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Consequences of Individual Differences in Brain Organization for Human Performance

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for

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This research note summarizes the work done during the first year of a four-year research program to identify how measurement of brain functioning, especially individual differences in brain functioning, can be used to understand and predict human performance in complex human-machine systems. A major objective of the completed work was to define measures which identify characteristics of individual brain functioning. The results suggest that electrophysiological measures have the greatest potential to measure performance-related

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aspects of brain functioning. Given the sensitivity of the electrophysiological measures to variation in brain functioning, and their potential as measures of workload, it is planned to include further evaluation of these measures in future work, as indices of performance-related aspects of brain functioning.

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PREFACE

The research described in this report represents the work of the first year of a four-year program conducted at the Georgia Tech Research Institute of the Georgia Institute of Technology under the technical supervision of Dr. Joanne Green. The research was performed in the Human Performance Branch of the Concepts Analysis Division of the Systems Engineering Laboratory. The technical representative for the U.S. Army Research Institute was Dr. George Lawrence.

The success of the research has depended heavily upon the important contributions of a number of individuals. The project has benefited from steadfast Georgia Tech management support provided by Mr. Robert P. Zimmer and Mr. William E. Sears, III. Invaluable technical assistance was made available through consultation with Dr. Charles M. Epstein, a neurologist at The Emory Clinic at Emory University. Major contributions to the performance of the experiments and the collection of data were made by Mr. Peter DeNatale, Ms. Gail Brickley and Ms. Joan Moore. The hardware and software design benefited significantly from the participation of Mr. Michael Cooper, an electrical engineering student at Georgia Tech.

SECTION I

EXECUTIVE SUMMARY

This report summarizes the work completed in the first year of a four-year research program aimed at identifying how measures of brain functioning, especially individual differences in brain functioning, can be used to understand and predict human performance in complex human-machine systems. The nature and characteristics of individual brain functioning are, at a minimum, important correlates of human performance, and are likely to have a more important role as mediators or determinants of the quality of human performance. Measures of brain functioning have potential for either supplementing, or perhaps replacing, more conventional measures, such as direct performance measures (e.g., accuracy) which provide relatively global descriptions, or subjective (self-report) measures which place additional workload on the operator.

Measures of brain functioning that assess or predict the quality of performance could contribute to overall system performance in a variety of ways. First, this capability can be applied to the system design process to help understand the impact of alternate designs. Second, improved procedures for quantifying and predicting aspects of human performance can be incorporated in adaptive systems to aid in decisions regarding the allocation of tasks to the human versus the machine component of the system. Finally, such measurement can be applied to a number of important training-related issues, including the measurement of performance during training and optimal training design.

A major objective of the completed work was to define measures for identifying characteristics of individual brain functioning. Although a variety of measures have been suggested, there is little evidence regarding the differential sensitivity of the measures and their relative value for application to more applied problems. The approach taken was to examine the sensitivity of each of the measures to differences in brain functioning between left and right-handed individuals. A major factor around which brain functioning is organized is the representation of language-related activity. In the great majority of right-handers, language representation is lateralized in the left hemisphere of the brain. In contrast, language representation in left-handers is more variable, with language frequently represented bilaterally or in the right hemisphere. It was assumed that, in order for a measure to be sensitive to individual differences in brain functioning, it should, at a minimum, be

sensitive to handedness group differences in brain functioning.

The measures that were examined included gross behavioral measures, finer performance measures, and electrophysiological measures of brain activity. The latter included spectral analysis of alpha activity, the level of which is inversely related to the level of brain activation, and analysis of event-related-potentials (ERPs). The electrophysiological data were collected while left and right-handed subjects performed a lexical decision task, a language-related task that should highlight handedness group differences in brain functioning.

The results suggest that the electrophysiological measures have the greatest potential for measurement of performance-related aspects of brain functioning. The analysis of alpha activity indicated that this measure was sensitive both to handedness group differences in brain functioning and to differences between the cerebral hemispheres in their relative involvement in lexical decision-making. Of great interest was evidence that the P300 component of the ERP was also sensitive to handedness and hemispheric differences. The amplitude of the P300 has been described by others as a measure of perceptual-central workload, a conceptualization which was supported by the present results. The measurement and prediction of operator workload is a critical to the design and performance of human-machine systems.

Given the sensitivity of the electrophysiological measures to variation in brain functioning, and their potential as measures of workload, it is planned that future work will include further evaluation of these measures as indices of performance-related aspects of brain functioning. One focus of the planned work will be the development of several psychometric models that can be applied to the assessment and prediction of operator workload. The research will involve two phases. During the first phase, a psychometric measurement procedure which assesses critical individual characteristics and allows specification of individual operator profiles will be developed. During the second phase, a psychometric prediction model which uses this profile to predict workload level will be developed. One focus of the work during the next year will be on the identification of the necessary profile components and of algorithms that can be used in a predictive model.

SECTION II

BACKGROUND TO THE PRESENT PROGRAM

A. Context for the Research and Overall Goal

Individual differences can dramatically impact the effectiveness of Army human-machine systems. The presence of subtle, but significant, unrecognized variation in individual characteristics can have profound effects on system functioning in critical conditions such as those encountered during battle.

Several approaches for minimizing the negative impact of individual differences are possible. One involves the development of "adaptive systems." In such systems, the functioning of the machine component adjusts, or adapts, to variation in human performance in a compensatory, supportive fashion to maintain the necessary quality of overall human-machine system performance. A second approach focuses on the development of training which attempts to bring individual skill to the level required to interact effectively with the machine.

The success of either of these approaches depends heavily on knowledge of the nature of individual characteristics and their variation. The lack of such knowledge can lead to the development of systems that fail to adapt to certain, critical human characteristics or to the development of training which fails to address certain skills critical to effective system functioning.

The overall goal of the present research program is to contribute to human-machine system effectiveness by identifying how measures of individual brain functioning can be applied to the understanding and prediction of individual variation in important aspects of performance. As upcoming discussion will indicate, there is substantial evidence of variation between individuals in a variety of aspects of brain functioning. This variation may have significant consequences for the quality of performance, especially human performance in complex, demanding, human-machine systems. The present research program aims to clarify the nature of these consequences and to identify measures of individual brain functioning that can be used to model and to predict human performance in complex systems.

B. Evidence of Variation in Brain Organization and Arousal

The purpose of the present program is to identify the consequences of individual differences in brain functioning.

At least two aspects of brain functioning seem relevant. One aspect is brain "organization," which will be used to refer to the location of neural areas specialized for certain important functions, e.g., for language processing. A second aspect is brain "arousal", which refers to the patterns of arousal occurring during task performance, particularly the extent to which the left versus the right hemisphere becomes aroused. Although the pattern of arousal may be closely related to the nature of brain organization, there is evidence that arousal may be somewhat independent of organization, as later discussion will point out.

A variety of evidence converges on the notion that there are subtle, yet distinct and important individual differences in brain organization. The bulk of the evidence comes from studies of language processing. While for the majority of individuals, language-related processing is heavily dependent upon the left hemisphere and visuospatial processing on the right hemisphere, handedness and sex have each been related to variation upon this fundamental organization. Both clinical and experimental studies suggest that among left-handers (as compared to right-handers), there is a greater frequency of bilateral and right hemisphere language representation (Galin, Ornstein, Herron, & Johnstone, 1982; Herron, 1980; Satz, 1980; Segalowitz & Bryden, 1983; Zurif & Bryden, 1979). Although the nature of sex differences in brain organization is somewhat more controversial (Buffery & Gray, 1972; Fairweather, 1976; Levy & Gur, 1980; McGlone, 1980), there is general agreement that such differences do exist.

An important basis for the notion that there are performance-related individual differences in brain arousal comes from the work of Levy, Banich, Burton, and Heller (1983). They propose that, "a large proportion of the variation among right-handed individuals in perceptual asymmetries arises from individual differences in characteristic and task-independent asymmetries of hemispheric arousal." They support their theory with a range of evidence from neurophysiological, electrophysiological, and behavioral studies. Their proposal is particularly important in that it implies that arousal asymmetry is a fundamental individual characteristic mediating a wide range of individual differences in performance and personality.

The idea that individual differences in brain arousal are related to individual differences in aspects of performance is further supported by the results of research supported by A.R.I. under a previous contract (contract #MD903-85-K-0178). This research investigated the hypothesis that, among right-handed males, between-individual variation in perceptual asymmetry in language tasks was related to variation in hemispheric arousal asymmetry. Variation in perceptual

asymmetry among this population is not predicted on the basis on brain organization, since the great majority of right-handed males has left hemisphere language representation. It was found that the degree of left versus right hemisphere arousal (arousal asymmetry), as assessed by electroencephalographic activity, was related to the quality of performance based on left versus right visual field stimuli (perceptual asymmetry). Detailed results are reported in Green, West, and Engler (1986).

C. Consequences of Variation in Brain Functioning

Given the existence of variation in brain functioning, an important question concerns the consequences of such variation for performance. It has been argued that the most common form of organization, lateralization of language in the left hemisphere and visuospatial functions in the right hemisphere, reduces the possibility for interference between these and other activities. Levy (1969) has argued that other patterns of organization, particularly bilateral representation of a function, may result in greater interference, causing cognitive deficits. There has been mixed experimental support for this idea (Briggs, Nebes, & Kinsbourne, 1976; Levy, 1969).

Other relevant research has examined whether groups differing in handedness or in sex also show cognitive differences, with the major focus being on verbal and visuospatial abilities. The results comparing handedness groups are complex and mixed, with some reporting differences (Bradshaw, Nettleton, & Taylor, 1981; Piazza, 1980) and others no difference (Hardyck & Petrinovich, 1977). Comparisons of males and females are also somewhat inconclusive, although they generally support the idea that males are superior at visuospatial tasks (Harris, 1978; McGee, 1979), and females at verbal output tasks (Harris, 1977; McGee, 1980).

Such results tend to question whether there is, in fact, a reliable relationship between variation in brain functioning and performance. There are, however, several problems with existing research. First, existing studies are not a very powerful test because they may not compare groups which do, in fact, differ in brain organization. While there is a greater frequency of atypical brain organization among left handers, a large proportion are likely to have brain organization similar to that of right-handers. There is a need for improved approaches to identifying individual differences in brain functioning.

A second problem is that existing studies have focused on verbal and visuospatial skills as measured in achievement tests or single-task conditions. For more applied purposes, there is a need for examination of a wider range of performance-related abilities in conditions more representative of those encountered by Army personnel.

D. Program Objectives and General Approach

The research presented in this report represents the first year of a four-year program designed to identify the relationship between individual differences in brain functioning and variation in significant aspects of individual performance. The objectives of the four-year program are as follows:

1) To define measures for identifying characteristics of individual brain functioning.

2) To identify how individual brain functioning is related to significant aspects of performance that affect overall human-machine system effectiveness.

3) To develop procedures for applying knowledge of such individual differences to increasing human-machine system effectiveness through improvements in adaptive system design or in personnel training.

To achieve these objectives, a collaborative, multidisciplinary approach is being applied, involving scientists from the Georgia Institute of Technology, Emory University, and Georgia State University trained in cognitive psychology, neurology, neuropsychology, and electrical engineering. Behavioral, neuropsychological, and electroencephalographic data are being collected to quantify individual brain organization and functioning. The experimental tasks that will be used to assess the consequences of these individual differences are being derived from cognitive research on fundamental aspects of human performance as well as consideration of Army needs. The work during the first year has focused on the first of the objectives previously defined.

SECTION III

EXPLORATION OF ELECTROPHYSIOLOGICAL DATA ANALYSIS

A. Introduction

One area of work during the past year has involved further study of electrophysiological data analysis to better understand the characteristics of different procedures that affect the present work. One consequence of this study has been the selection and evaluation of an algorithm for spectral analysis that uses more modern procedures and that can be applied to provide estimates of spectral power with high resolution even when the sample size is very small. A second focus of effort which will be described has involved analysis of the stability of measures of alpha activity. Such stability is highly desirable if measures of alpha activity at one time are to be used to make inferences about the quality of performance at another time.

B. Review of Spectral Estimators for Short Time Samples

Throughout this report, reference is made to the "spectrum" of the signal, either implicitly, or explicitly. The spectrum, or power spectrum, of a signal is the graph, or curve that specifies the amount of power that the signal possessed over a range of frequencies. When the power in the alpha band is said to be, for example 1 Watt, what is meant is that the total area under the power spectrum curve (which is in Watts per Hertz) between 8 and 12 Hertz is 1 Watt.

Mathematically, the power spectrum of a deterministic signal (a signal with no random components) is described by the square of its Fourier Transform. For random signals, the power spectrum is described by the Fourier Transform of the signal's autocorrelation function. Since autocorrelation involves the statistical operation of expectation, finding the power spectrum of a random signal poses a special problem. In an experimental system, generally only a short sample, or several short samples of a random signal may be collected, but in order to calculate the expected value, an infinite (or at least a large) sample set would be necessary. A common approach to this problem is to simply transform the sampled data, and disregard the fact that the data are most appropriately described by a random process. Under certain conditions (e.g., low noise) this works well, but sometimes it can produce misleading results.

Much of the analysis reported in this report is based on the use of the Discrete Fourier Transform (DFT). (The outputs

of the DFT's were averaged to approximate the calculation of the expected value). This transform is widely accepted by the EEG community as being a useful tool for the analysis of the frequency content of EEG signals. However, it is not the only tool available. Indeed, there are times when the DFT is an excellent tool for spectrum estimation, and others when its performance may be inferior to other "modern" or model-based spectrum estimation techniques. Appendix A presents an in-depth look at modern spectral estimation techniques, and compares them to the DFT. The results of this comparison will be summarized here. However, the interested reader is encouraged to study the appendix for further details.

The DFT is a discrete time version of the Fourier Transform for use with discrete time signals, or sampled data. It may be efficiently calculated on digital computers via an algorithm known as the Fast Fourier Transform (FFT). The results of an FFT are identical to that of the DFT; the only difference is that the FFT uses an efficient algorithm to get the same answer. A more complete name for the FFT would be the Fast Discrete Fourier Transform. The existence of the efficient FFT algorithm has led to its widespread use for signal analysis in virtually all aspects of science and engineering where sampled data systems and digital computers are employed.

There are many advantages to using the FFT over other spectrum estimation techniques. It is always stable, the expected value of its output is proportional to the true power spectrum, and its behavior is well understood. Unfortunately, its output estimate tends to have a high variance (when applied to noisy signals), and its frequency resolution decreases as the sample interval time decreases. In fact, the frequency resolution of the DFT is equal to the reciprocal of the observation time (or sample length). Based on this relationship, it can be seen that at least 0.25 sec of data are required in order to estimate the power in a single EEG band which is nominally 4 Hz wide. Further, in the FFT, small signals may be masked by nearby signals of larger power. In terms of EEG, this means that a large DC component in the delta band could cause a bias in the estimate of the energy in theta band. These shortcomings in the FFT led to the investigations of modern spectrum estimation as detailed in Appendix A. Modern techniques have the capability of producing higher resolution, with more consistent estimates which may be beneficial for limited sample time EEG analysis.

An easy way to think of the modern model-based techniques described in Appendix A is in terms of filters. Most scientists are comfortable when thinking about bandpass or band-reject filters. If white noise (a signal with constant power at all frequencies) is input to a bandpass filter, then

the spectrum of the signal at the output of the filter will have the same shape as the filter "transfer function". Clearly, any output shape could be obtained by just "designing" a filter with the correct "transfer function". This is exactly how modern spectral estimation techniques work -- they attempt to find the filter that produces an output spectrum that best matches the spectrum of the actual signal. As each new time sample becomes available to the estimator it dynamically adjusts the filter coefficients to select the best matching filter. Because of this dynamic adjustment to new data, these techniques are sometimes referred to as adaptive. Clearly, the assumption here is that a reasonable model for the signal is the so called ARMA (AutoRegressive Moving Average) process, that is, a signal that could have been generated by a filter driven by white noise.

In Appendix A, a summary of several different modern spectrum estimation techniques is presented (although all are philosophically similar, different algorithms are used to select the filter coefficients). Next, these techniques are analyzed in light of the specific application -- limited sample time EEG analysis. Based on this, one technique, the AutoRegressive Least Squares (ARLS) technique, was selected as the best for this application. Under this project, this technique was implemented in a FORTRAN program, and its behavior studied. Appendix A also presents a comparison of this estimator with the FFT for a variety of random and deterministic signals. Also, some actual EEG spectra are presented as calculated by both the FFT and the ARLS method. In the last section, some discussion is presented regarding model order selection. Overall, the results suggest that the ARLS method may have considerable merit in limited sample time EEG analysis. First, its spectral resolution is superior to that of the FFT. Next, its spectral estimate is far more pleasing to look at since it produces a smooth curve rather than the sequence of "jumpy" samples of the FFT. In another test, the output of the ARLS algorithm was summed over the 4Hz EEG bands, and compared to the FFT results for lexical decision task data. These two methods of analysis produced highly correlated results suggesting that the two methods are consistent. One may ask "If the two methods give the same answer, then why go to the trouble of using the ARLS method?" The answer is that the ARLS method may be used to gain further insight into EEG spectra. For instance, the ARLS method provides information on not only how much energy is in the alpha band, but also on where the peak is, and how sharp it is. For short data records there may be no estimate of these parameters from the FFT method.

C. Stability of Measures of Alpha Activity

A desirable characteristic of a measure of individual differences is that the measure be a stable measure. A useful measure should provide similar values when applied at different times but to similar conditions. This is particularly important if the measure is to be used to make inferences about the quality of human performance to take place at another time.

The purpose of the present investigation was to examine the stability of the FFT estimate of alpha activity. The analysis was done by comparing measures of alpha activity obtained from ten right-handed subjects each of whom participated in two testing sessions containing identical conditions -- a lexical decision task, a relaxation condition, and a reading condition. During each testing session, electroencephalographic (EEG) activity was recorded from three recording locations (temporal, central, and parietal) over each cerebral hemisphere. The conditions of testing and the method of EEG data analysis used to infer alpha activity are presented in Appendices B and C, respectively.

Correlations were computed between measures of alpha activity obtained in the first session and those obtained during the second session. The results are shown in Table 1. For the lexical decision task, the stability of alpha measured during pre- and post-stimulus intervals was examined separately. For the pre-stimulus interval, between-session alpha was highly significantly correlated for all six recording locations. However, for the post-stimulus interval, the measure of alpha correlated significantly only for recording at the left temporal location.

For the Read Condition, measures of left hemisphere alpha were significantly correlated for all three recording locations, but measures of right hemisphere alpha were not. For the Relax Condition, left hemisphere measures were significantly correlated, but for the right hemisphere, only the right parietal measure was significantly correlated between sessions.

The results indicate some variability in the stability of alpha as a function of testing condition, recording location, and interval of alpha analysis. Alpha is very stable for the pre-stimulus measures from either hemisphere during the lexical decision task and for the left hemisphere measures during the Read and Relax Conditions.

In general, measures of left hemisphere alpha activity were more stable than those of right hemisphere activity. A likely explanation for some of the variability in alpha

TABLE 1

Between-session Correlations in Alpha Activity.

Hemisphere-->	Left			Right		
Recording Location-->	Temp.	Cent.	Par.	Temp.	Cent.	Par.
Condition						
Lexical Decision Pre-stimulus	.886**	.823**	.880**	.820**	.840**	.947**
Lexical Decision Post-stimulus	.931**	.391	.067	.513	.252	.273
Read	.764*	.959**	.925**	.524	.587	.561
Relax	.615*	.698*	.745**	.486	.326	.725**

* $p<0.05$ (one-tailed)
** $p<0.01$ (one-tailed)

stability is that it is related to the degree of variability in the underlying mental activity. Within the lexical decision task, it can be argued that the variety of stimulus conditions (e.g., left visual field concrete word, right visual field nonword, etc.) evoked mental activity that was more variable during the post-stimulus interval than that which occurred during the pre-stimulus interval, when the subject was highly prepared to process the imminent stimulus. Greater post-stimulus variability in mental processing most likely accounts for the poorer stability of post-stimulus alpha measures as compared to pre-stimulus measures. Similarly, for the Read Condition, the greater stability of the left hemisphere measures can be attributed to more consistent engagement of that hemisphere in reading, while the right hemisphere was less task-engaged and therefore exhibited more variable activity.

SECTION IV

ADDITIONAL DATA COLLECTION: CONCEPTUAL APPROACH AND METHOD

A. Introduction

Another major focus of effort has been the collection of additional behavioral, neuropsychological, and electrophysiological data to supplement that previously collected (see Green, West, & Engler, 1986) for use in identifying, and developing measures of individual differences in brain functioning. In Section IV are described the conceptual approach and method for this data collection.

B. Conceptual Approach

A variety of measures have been suggested as relating to individual differences in brain organization. These include measurement of gross behavioral features (e.g., handedness, footedness, finger tapping speed, eye dominance), finer measures of performance (e.g., reaction time), and electrophysiological measures of brain functioning (e.g., ongoing EEG activity, event-related potentials (ERPs)). There is, however, little agreement on the differential usefulness of each of these measures, and, in particular, on which measures are most useful for application to more applied problems.

The purpose of the data collection during this year was to complete the collection of a set of data that could be used to examine the sensitivity of a variety of measures of individual differences in brain organization. The ultimate goal was to select a measure that had the greatest potential for enhancing the measurement of human performance in conditions of interest to the Army. Special interest was focused on the usefulness of electrophysiological measures of brain activity, notably spectral analysis of EEG activity and analysis of ERPs, since these provide direct measures of brain activity. A number of behavioral measures were also included to provide a larger range of dimensions along which individual differences in brain organization could be studied.

The approach was to compare the brain activity of left and right-handers during performance of a lexical decision task. As described in Section II, individuals varying in handedness also vary in the extent to which language-related functioning is lateralized to the left hemisphere. While language is lateralized in the left hemisphere of most right-handers, the representation of language in left-handers is more variable, frequently including bilateral or right hemisphere representation. The representation of language-

related functioning is fundamental to brain organization and is likely to be a primary factor governing the representation of a number of other important functions.

One important focus of data analysis was the ability of each measure to detect handedness group differences in brain functioning. It was assumed that in order for a measure to be potentially useful for assessing individual differences in brain functioning, it should, at a minimum, be sensitive to handedness group differences in language lateralization. Therefore, for each measure, the data of left and right-handed samples were compared.

In addition to the lexical decision task, two additional conditions, a Relax Condition and a Read Condition were included for purposes of comparison. It was hypothesized that measures sensitive to handedness group differences should also detect such differences for the Read Condition, another language task, but not for the Relax Condition.

C. Method

1. Subjects

The subjects were forty experimentally naive, Georgia Tech male undergraduates. Twenty were self-reported right-handers, sixteen of whom had been tested during the spring of 1986 under the previous contract (MDA903-85-K-0178). Ten of these right-handers were tested in two identical testing sessions to obtain data for the reliability analysis. Four additional right-handers and twenty self-reported left-handers were tested during the spring of 1987 under the present contract. These subjects were each tested for one session.

2. Apparatus

A diagram of the system used to control stimulus presentation and to collect data is included as Figure 1. Major components of the system include a Grass Instruments Company eight channel EEG machine, a PDP 11/23 computer used to store EEG data, an IBM Personal Computer (PC) used to control stimulus presentation and to collect reaction time data, and an IBM AT used for data analysis. Factors governing the design of the EEG data collection system and its special characteristics are detailed in Green, West, and Engler (1986).

The IBM PC is equipped with a Tecmar Graphics Board and a Quadchrome color monitor used to present visual stimuli for the eye movement calibration, for the Reading condition, and for the lexical decision task. The PC also controlled all interval timing and, when appropriate, recorded reaction time

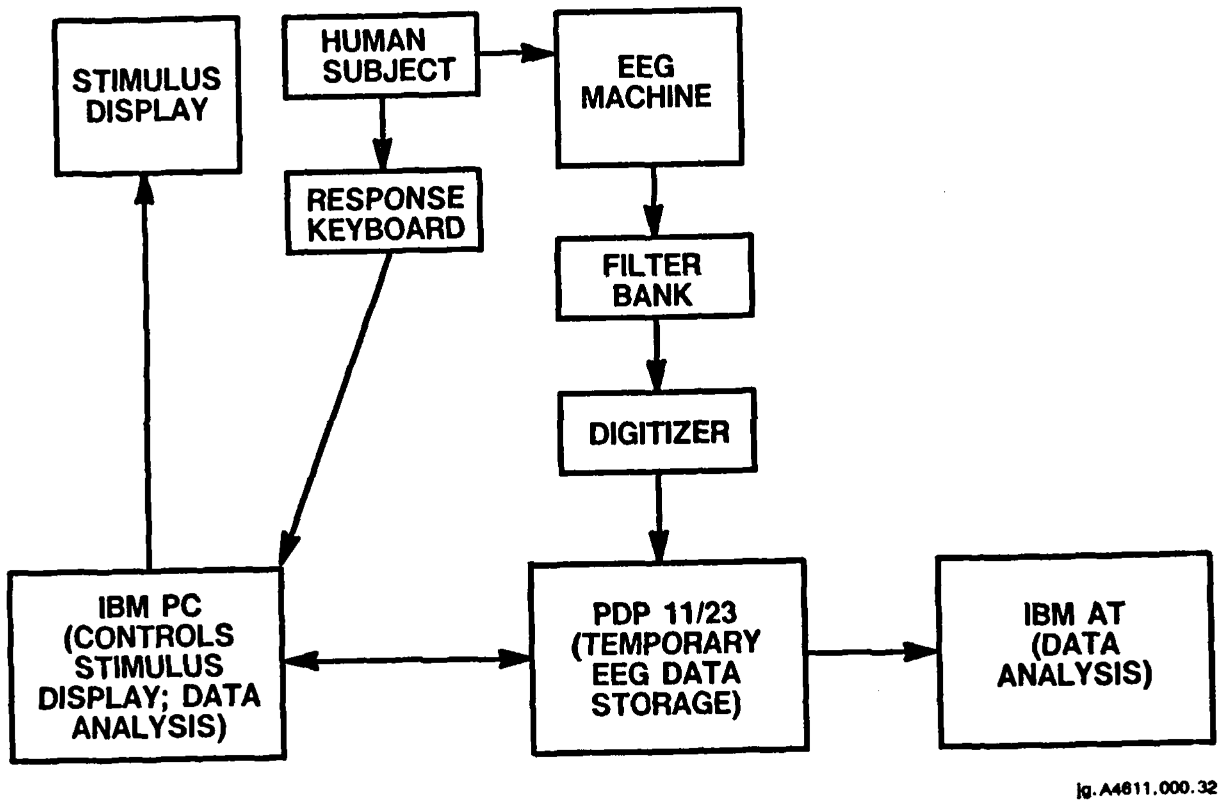

Figure 1. Diagram of the Testing and Data Analysis System.

in ms. The color monitor was set to display white stimuli on a dark gray background. The graphics-controlling software for the lexical decision task, where timing was critical, was specifically designed to minimize and control time variations due to the 16.67 ms refresh time of the color monitor's cathode ray tube.

The subject sat at a table before the display and, when appropriate, placed his head in a headrest which positioned the eyes 50.0 cm away from the center of the display. During the lexical decision task, the subject responded by using two 4.9 by 2.0 cm microswitch keys mounted on a keyboard sitting on the table. The testing room was dimly lit.

3. <u>Procedure</u>

The order of events for each test session is outlined in Table 2. These events were identical to those used in the previous A.R.I. research (Green, West & Engler, 1986) with the exception that a second Relax Condition following the lexical decision task was eliminated, and subjects were tested for only one session. The general procedure is described here; details are provided in Appendix B.

The purpose of the behavioral assessment was to collect data on some dimensions which have been proposed as indices of brain organization (see Bryden, 1982). The indices were handedness, eye dominance, finger tapping speed, parental handedness, and foot dominance. The method used to measure each of these is described in Appendix C. Appendix D indicates the age, handedness score, footedness score, tapping scores, parental handedness, and eye dominance for each subject.

Following the behavioral assessment, the electrodes used for EEG data recording were attached to the scalp of the subject. Using the International 10-20 measurement system (Jasper, 1958), electrodes were attached in locations T3, C3, P3, T4, C4, P4, using a linked ear reference. An electrode was attached to the chest to monitor cardiac activity that might produce artifacts in the EEG data. An electrode was also attached to the outer canthus of each eye to allow recording of horizontal eye movements. Data from an eye movement calibration was used to eliminate trials on the lexical decision task when an inappropriate eye movement had occurred.

Each subject then participated in a Relax Condition, a Read Condition, and the lexical decision task. During the four minute Relax Condition, the subject was instructed to place his head in the headrest, to close his eyes, and to relax, keeping all movement to a minimum to prevent EEG

TABLE 2

Events in Each Test Session.

1. Behavioral analysis
2. Attachment of electrodes
3. Eye movement calibration
4. Relax Condition
5. Read Condition
6. Lexical decision task
7. Collection of calibration data

artifacts. During a four-minute Read Condition, the subject placed his head in the headrest and read text presented on the visual display before him. Immediately following the Read Condition, the subject was asked a series of eight questions to validate that he'd read and comprehended the presented material.

Details concerning the stimuli and procedure for the lexical decision task are included in Appendix B. To summarize, this task required subjects to decide, on each test trail, whether a four-letter string presented briefly in the left or right visual field comprised a word or nonword. Half of the presented items were nonwords and half were words; within the latter, half were abstract words and half were concrete words. The subject's response was indicated with a within-hand choice response, with responding hand (left or right), and response assignment (index or middle finger for "word" stimuli) counter balanced across subjects. Subjects were presented with 3 blocks of 64 trials each, and were encouraged to keep their error rate below twenty percent.

During performance of the lexical decision task, EEG data collection for each trial was initiated by the keypress indicating visual fixation at the beginning of the trial and was terminated by the keypress response indicating the subject's word-nonword decision. During the Read and Relax conditions, EEG data were collected and stored for alternate four-second intervals.

SECTION V

RESULTS

A. Behavioral Assessment

1. Handedness Scores

The handedness score for each subject is contained in Appendix D. The mean and standard deviation for each group are shown in Table 3. There was a significant difference in the handedness scores of the two groups ($t(38) = 14.27$, $p<0.01$).

2. Footedness

The footedness score of each subject is shown in Appendix D, and the frequency distribution of footedness scores for each handedness group is shown in Table 4. There was a significant difference in the footedness scores of the two groups ($X^2(3) = 14.54$, $p<0.01$), with the right-handers being more right-footed than the left-handers.

3. Parental Handedness

It was originally intended that the family handedness of each subject be assessed. However, subjects reported great uncertainty concerning the handedness of siblings, grandparents, etc., so only the data concerning parents is considered to be reliable. The handedness of biological parents for each subject is indicated in Appendix D. Very few of the subjects reported at least one left-handed parent, and none had two left-handed parents. There were no handedness group differences in parental handedness.

4. Finger Tapping

The mean tapping speed for each subject is contained in Appendix D. The mean tapping speed and standard deviation for each hand and for the hand difference for each handedness group are shown in Table 5. For the right-handers, the right hand tapping score was significantly greater than the left hand scores ($t(19) = 6.31$, $p <0.01$). This difference was not significant for the left-handers. There was significant variation between handedness groups in the hand difference scores ($t(38) = - 4.03$, $p<0.01$).

4. Eye Dominance

The eye dominance of each subject is shown in Appendix D, and the frequency distribution for each handedness group in Table 6. There was no significant difference in the eye dominance of the two groups.

TABLE 3

Handedness Scores for Each Handedness Group: Mean and Standard Deviation (S.D.).

	Mean	S.D.
Right-handers	50.6	3.8
Left-handers	27.1	6.1

TABLE 4

Frequency Distribution of Footedness Scores for each Handedness Group.

	Footedness Score			
	1	2	3	4
Right-handers	0	0	3	17
Left-handers	0	10	5	5

TABLE 5

Mean and Standard Deviation (S.D.) of Tapping Scores for Each Handedness Group.

	Left-handers		Right-handers	
	Mean	S.D.	Mean	S.D.
Left hand	55.0	6.0	51.9	6.1
Right hand	53.2	8.1	56.4	6.6
Right-left hand	-1.8		4.5	

TABLE 6

Frequency Distribution of Eye Dominance for Each Handedness Group.

	Eye Dominance	
	Left	Right
Right-handers	8	12
Left-handers	11	9

5. Discussion of Results of Behavioral Assessment

For the most part, the gross behavioral measures revealed handedness group differences as expected. Both handedness and footedness scores indicated that the left-handers were more left-dominant and the right-handers more right-dominant. The handedness group difference in footedness scores is of particular interest. It has been argued that footedness is perhaps a better measure of motor dominance than is handedness because the former is less culturally influenced (Searleman, 1980). However, footedness differences have not been frequently measured or reported.

Tapping scores revealed no overall handedness group differences in fine motor control, but greater equivalence between the two hands for the left-handers. For the right-handers, the right hand fine motor control was superior to that of the left hand.

It appears that eye dominance is not a useful measure of individual differences in brain functioning. There were no handedness group differences for this measure. Somewhat surprising was the infrequency of reports of left-handed parents, especially for the left-handers. Others have reported an increase in the frequency of left-handed parents among left-handers, relative to right-handers. The infrequency of left-handed parents for the present sample questions either the validity of the report of parental handedness or the overall representativeness of the left-handed sample in this respect.

B. Analysis of Lexical Decision Task Performance Data

1. Reaction Time

This analysis focused on the reaction time data collected during performance of the lexical decision task. Each subject's data were scrutinized for possible speed-accuracy tradeoff. This was done by comparing the median left and right visual field reaction time for each subject, and determining whether the performance advantage inferred from this was consistent with that implied by comparison of the average percentage of error for the left and right visual field. If the percentage of error differed by ten percent within the visual fields and suggested that error was greater in the visual field associated with the slower median

reaction time, then occurrence of a speed-accuracy tradeoff was inferred. None of the subjects were eliminated for this reason.

For each subject, the median reaction time was computed for each stimulus type (concrete word, abstract word, nonword) by visual field (left, right) condition, collapsing over the three test blocks. In computing the median, only trials for which there were valid EEG data were included. That is, reaction times for trials associated with EEG artifact or eye movement were excluded. The corresponding average percentage of error was also calculated.

Individual subject data are contained in Appendix E. The means are shown in Table 7. The difference between overall median left and right visual field reaction time represents the perceptual asymmetry of each subject. Analysis of variance (ANOVA) was done on the median reaction times using stimulus type and visual field as within-subjects variables, and handedness and responding hand as between-subjects variables. There were main effects of visual field ($F(1,36) = 37.72$, $p<0.01$) and of stimulus type ($F(2,35) = 26.83$, $p<0.01$), but no interaction. Reaction time to stimuli in the right visual field (749 ms) was faster than that to stimuli in the left visual field (811 ms). Reaction time was similar for abstract words (746 ms) and concrete words (738 ms), but slower for nonwords (854 ms). This is similar to results obtained in previous research (Green, West, & Engler, 1986).

There was also a handedness by type by visual field interaction ($F(2,72) = 3.86$, $p<0.05$). The right visual field advantage tended to be larger for left-handers than for right-handers for both word stimulus types. For nonwords, however, right-handers showed a larger right visual field advantage.

2. Percentage of Error

The mean percentage of error for each subject is included in Appendix E. The means for each condition are shown in Table 7. Analysis of variance was done on an arcsine transformation of percentage of error using the same design as that for the reaction time data. There was significantly less error for the right visual field (11.2%) than for the left visual field (18.5%) $F(1,36 = 36.19$, $p<0.01)$. There was significantly less error for concrete words (12.1%) than for abstract words (15.0%) than for nonwords (17.3%, $F(2,72) = 8.31$, $p<0.01$). There was a visual field by stimulus type interaction ($F(2,72) = 6.08$, $p <0.01$). The right visual field advantage was greater for abstract and concrete words than for nonwords.

TABLE 7

Mean Reaction Time(ms) and Percentage of Error for Lexical Decision Task.

Reaction Time:

Stimulus Type-->		Abstract Word		Concrete Word		Nonword	
Visual Field-->		LVF	RVF	LVF	RVF	LVF	RVF
Handedness	Responding Hand						
Left-handers	Left	769	706	779	687	852	821
	Right	846	695	777	693	917	900
Right-handers	Left	718	687	742	690	848	795
	Right	806	749	798	745	882	818

Percentage of Error:

Left-handers	Left	22.9	14.2	21.7	10.0	22.5	19.0
	Right	20.0	11.3	17.9	5.8	15.6	14.2
Right-handers	Left	14.2	7.5	12.5	6.7	16.9	12.9
	Right	20.4	9.6	16.3	6.3	20.6	16.7

There was also a near-significant main effect of handedness ($F(1,36) = 3.51$, $p < 0.10$). Left-handers tended to have a higher percentage of error than right-handers. There was a significant interaction between handedness and responding hand ($F(1,36) = 5.74$, $p < 0.05$). For right-handers, there was little difference in percentage of error between the left hand (14.1%) and the right hand (15.0%). However, for the left-handers, the left hand had a greater percentage of error (18.4%) than did the right hand (11.8%).

3. Discussion of Lexical Decision Task Performance Data

The performance data provides strong evidence of left hemisphere specialization for language-related functioning. Performance was faster and more accurate for right visual field-left hemisphere stimuli. However, neither the reaction time nor the error data provide evidence of handedness group differences in language lateralization. The advantage for the right visual field-left hemisphere stimulus presentation did not vary significantly as a function of handedness group.

This result is, however, not inconsistent with that of similar studies. Several studies using either reaction time (Lieber, 1976) or accuracy (Chiarello, Dronkers, & Hardyck, 1984) have failed to find handedness group differences in the magnitude of the right visual field-left hemisphere advantage observed for a lexical decision task. In contrast to these are the results of Bradshaw, Gates, and Nettleton (1977), who reported that the right visual field reaction time advantage was present for right-handers but not for left-handers. Since they tested only left-handers with at least one close left-handed relative, it could be argued that family left-handedness is important in determining whether left-handers show a reduced right visual field advantage. The importance of this factor is, however, questioned by the results of Chiarello et al. who found no relationship between the magnitude of visual field differences and either subject handedness or family handedness. It appears that behavioral performance on the lexical decision task may not provide a very sensitive or reliable index of handedness group differences in brain organization.

C. Spectral Analysis of Brain Activity

1. Approach to Analysis of EEG Data

Each data sample was reviewed to eliminate samples contaminated by artifact or during which an inappropriate eye movement occurred. A Fast Fourier Transform (FFT) was used to assess power within the alpha band. The level of power within the alpha band is inversely related to the degree of brain

activation. Increases in the level of brain activation are associated with reduction in the level of alpha activity. Details concerning the analysis of alpha are included in Appendix F, including the number of valid samples per condition.

2. Computation of Asymmetry Score

A major interest in this research is the relationship between asymmetry in brain hemisphere functioning and aspects of human performance. Therefore, in applying spectral analysis to this question, the focus was on the relative alpha activity of the right versus the left hemisphere.

To examine alpha asymmetry, an asymmetry score was computed. For each subject for each recording location, this score was computed by dividing the difference between right and left hemisphere alpha by the sum of the right and left hemisphere alpha (R-L/R+L). Use of this score normalizes the data for individual differences in absolute alpha that are not of interest in this research, e.g., for differences in absolute alpha due to skull thickness. Increasingly more positive scores indicate increasingly less left as compared to right alpha, i.e., increasingly greater left, relative to right, hemisphere activation. Negative scores indicate that alpha is less for the right, than for the left, hemisphere.

3. Relax Condition

This analysis focused on the EEG data collected during performance of the Relax Condition. The median alpha for each subject for each hemisphere and recording location is included in Appendix G. The means for alpha asymmetry are shown in Table 8. An ANOVA of alpha symmetry with handedness and location as factors indicated that the overall alpha asymmetry (.0548) was significantly different from zero ($F(1,38) = 6.08$, $p<0.05$). There was, however, no effect of handedness. There were no other significant effects.

4. Read Condition

This analysis focused on the EEG data collected during performance of the Read Condition. The median alpha for each subject for each hemisphere and recording location is included in Appendix H. The alpha asymmetry means are shown in Table 9. An ANOVA including handedness and location as factors indicated that the overall alpha asymmetry (.0270) was not significantly different from zero. There was, however, a near significant effect of handedness ($F(1,37) = 3.43$, $p<0.10$). As can be seen in Table 9, the mean alpha asymmetry score for the right-handers (.0692) suggested greater left hemisphere

TABLE 8

Relax Condition:
Alpha Asymmetry.

Recording Location-->	Temporal	Central	Parietal
Handedness Group			
Left-handers	.0326	.0400	.0659
Right-handers	.0478	.0609	.0817

TABLE 9

Read Condition:
Alpha Asymmetry.

Recording Location-->	Temporal	Central	Parietal
Handedness Group			
Left-handers	-.0044	-.0018	-.0295
Right-handers	.0945	.0950	.0182

activation while that of the left-handers (-.0512) suggested greater right hemisphere activation.

5. Lexical Decision Task

This analysis focused on the EEG data collected during performance of the lexical decision task. Of particular interest to later discussion is the fact that for the lexical decision task, alpha was estimated for the 250 ms interval just before stimulus onset (pre-stimulus interval) and for the 250 ms interval immediately after stimulus onset (post-stimulus interval). The pre-stimulus interval represents a period when the subject should be aroused to process the stimulus. The post-stimulus interval represents a period when the subject is actively processing the stimulus.

For each subject, the median alpha was computed for each recording time (pre- or post- stimulus), by recording location (temporal, central, or parietal) by hemisphere (right or left) condition, collapsing over the three test blocks. The data for each subject are included in Appendix H.

The mean alpha asymmetry for each recording location by recording time by responding hand by handedness group condition is shown in Table 10. An ANOVA including these variables as factors indicated that the asymmetry score (.0473) was significantly different from zero ($F(1,36) = 6.85$, $p<0.01$). The left hemisphere was significantly more activated than the right hemisphere. There was a significant effect of handedness ($F(1,36) = 5.53$, $p<0.05$), with the right-handers showing greater asymmetry (.0898) than the left-handers (.0048). These was also a significant location effect ($F(2,72) = 4.54$, $p<0.05$), with the asymmetry being almost non-existent at the temporal location (-.0002), but present at the central (.0627) and parietal (.0794) location.

It was of interest to examine whether the alpha asymmetry associated with the lexical decision task was different from that present during other conditions, particularly during the Relax Condition, during which there also was an overall alpha asymmetry. To examine this, for each subject for each recording location and recording time, the alpha asymmetry for the same recording location during the Relax Condition was subtracted from the alpha asymmetry during the lexical decision task. The resulting scores will be referred to as the alpha asymmetry shift scores. Positive values indicate that during the lexical decision task, there was a shift toward relatively greater left (than right) hemisphere activation. Negative scores indicate that there was a shift toward relatively greater right (than left) hemisphere activation. The mean shift scores are shown in Table 11.

TABLE 10

Lexical Decision Task:
Alpha Asymmetry for each Condition

Handedness	Responding Hand	Recording Time	Recording Location Temporal	Central	Parietal
Left	Left	Pre-	-.0767	.0287	.0329
		Post-	-.0788	.0746	.0423
	Right	Pre-	-.0754	-.0098	.0124
		Post	-.0594	.0681	.0986
Right	Left	Pre-	.0298	.0574	.0678
		Post-	.0905	.0860	.1250
	Right	Pre-	.1170	.1128	.1382
		Post-	.0516	.0834	.1178

TABLE 11

Lexical Decision Task:
Shift in Alpha from Relax Condition.

Handedness	Responding Hand	Recording Time	Recording Location Temporal	Central	Parietal
Left	Left	Pre-	-.1354	-.0337	-.0269
		Post-	-.1374	.0122	-.0175
	Right	Pre-	-.0818	-.0270	-.0598
		Post	-.0657	.0509	.0264
Right	Left	Pre-	-.0359	-.0063	.0481
		Post-	.0247	.0222	.1053
	Right	Pre-	.0874	.0550	-.0052
		Post-	.0220	.0256	-.0256

The shift scores were subject to an ANOVA using handedness, recording location, recording time, and responding hand as factors. The overall shift in asymmetry was not significantly different from zero. However, there was a near-significant effect of handedness ($F(1,36)=3.79$, $p<0.10$). For the right-handers, the shift in asymmetry tended to be in the direction of relatively greater left hemisphere activation, while for the left-handers, the shift tended to be in the opposite direction. The fact that the asymmetry shifts of the two handedness groups were in the opposite direction probably accounts for the absence of a significant overall asymmetry shift.

6. Discussion of Results of Spectral Analysis

In general, the results provide evidence of alpha asymmetry for each of the three conditions, and of handedness group differences in alpha asymmetry for the two language-related conditions. For the Relax Condition, the left hemisphere is more activated that is the right hemisphere. This is consistent with other results indicating greater right hemisphere alpha activity during relaxation. There is, however, no handedness group difference in the alpha asymmetry. Since there is no reason to hypothesize handedness group differences during relaxation, the between-group similarity in alpha asymmetry is to be expected.

For the Read Condition, there is no overall alpha asymmetry, which is perhaps surprising given the heavy involvement of the left hemisphere in reading. However, the absence of overall asymmetry seems to occur because the left-handers and right-handers are tending to exhibit opposite asymmetries, causing the overall asymmetry for the two groups combined to be minimal. The trend towards greater left hemisphere activation among the right-handers and greater right hemisphere activation among the left-handers is consistent with the idea that right-handers are more left hemisphere language lateralized, and left-handers are more heterogeneously lateralized, frequently exhibiting bilateral or right hemisphere language lateralization.

For the lexical decision task, there was also evidence of handedness group differences in brain organization. There was an overall alpha asymmetry indicating greater left hemisphere activation, but also greater asymmetry for the right-handers than for the left-handers. The handedness group difference provides evidence that the brain activation during the lexical decision task was not identical to that during the Relaxation Condition. In that condition, there was an overall alpha asymmetry but no handedness group difference in asymmetry. The analysis of the asymmetry shift scores further supports

the notion that the lexical decision task evoked task-specific activation and handedness group differences in this activation. Comparing the lexical decision task alpha asymmetry to that of the Relaxation Condition, for the right-handers, the shift in activation tended towards greater left (relative to right) hemisphere activation; for the left-handers, the opposite was true. The nature of these shifts is consistent with the hypothesized handedness group differences in language lateralization.

D. Analysis of Event-Related Potentials (ERPs)

1. Introduction

Because the ERP has not previously been used in this research, a brief introduction concerning its nature and value is necessary. The event-related potential is a specific, time-locked electrical response of the brain to the occurrence of a stimulus. In contrast to ongoing EEG activity, the ERP is of considerably smaller voltage. Signal averaging techniques are generally used to discriminate it from ongoing EEG activity.

The ERP appears as a waveform comprised of a series of components. Considerable research has been devoted to identifying the meaning of these components. Early components, up to about 250 ms following the stimulus, are referred to as "exogenous" components, and are obligatory responses of the sensory system generally related to physical characteristics of the stimulus, e.g., its intensity. In contrast, the occurrence of later, "endogenous" components is not obligatory and depends upon the occurrence and nature of higher-level, more cognitive processes. Of particular interest for the present purposes is evidence of lateral asymmetries in the ERP that correspond to task-related functional lateralization (Galin & Ellis, 1975; Shucard, Shucard, & Thomas, 1977), and of a relationship between attention and an endogenous, positive, component occurring about 300 ms after stimulus onset, known as the P300.

In the present research, it was decided to examine the ERP associated with the lexical decision task to see if it might be useful for assessing individual differences in brain functioning. This was very much an exploratory analysis since there has been little research examining individual differences, including handedness group differences, in the ERP.

2. Method

Since the ERP is of consiaerably smaller magnitude than ongoing EEG activity, special procedures must be used to

discriminate it. In the present case, signal averaging was used to discriminate the ERP of each subject. The principle behind signal averaging is that the ongoing EEG behaves like random background noise and, over repeated trials, averages to zero, or at least to a baseline level, allowing the non-random, stimulus-locked ERP to emerge.

For each subject, the EEG data for all correct, non-artifact-contaminated trials were averaged. Such averaging was possible because the collection of EEG data began at a uniform time 500 ms prior to stimulus onset. The ERP of two subjects (Subjects 35 and 40) could not be included because of deterioration of the magnetic tape on which the raw EEG data had been stored.

3. Results

Examination of the ERP for each subject revealed that the most prominent feature was the presence of a large positive component occurring between 200-400 ms after stimulus onset. The component was discriminable only at the central and parietal locations, so further analysis was focused here.

The component was quantified in two ways, illustrated in Figure 2. First, the time of the peak of the component was measured. Second, the amplitude of the component was measured. This was done by identifying the peak amplitude and subtracting the baseline amplitude, assessed as the ERP amplitude at stimulus onset.

The peak time and amplitude for each subject for each hemisphere are included in Appendix J. The mean peak times and amplitudes as a function of handedness, hemisphere, and recording location are shown in Table 12. Figures 3 through 6 illustrate the ERP averaged within each handedness group for each hemisphere and recording location.

Analyses of variance were done using handedness and responding hand as between-subjects factors and hemisphere and recording location as within-subjects factors. For the analysis of peak amplitude, there was a significant effect of hemisphere ($F(1,34)=23.27$, $p<0.01$), with the left hemisphere peak amplitude (34.74) being smaller than the right hemisphere peak amplitude (42.50). There was also a significant effect of location ($F(1,34)=18.14$, $p<0.01$), with the peak amplitude being lower at the central location (35.02) than at the parietal location (42.23).

There was a significant interaction between handedness, hemisphere, and recording location ($F(1,34)=4.61$, $p<0.05$). As can be seen in Table 13, for the central location, the difference between the right and left hemisphere peak

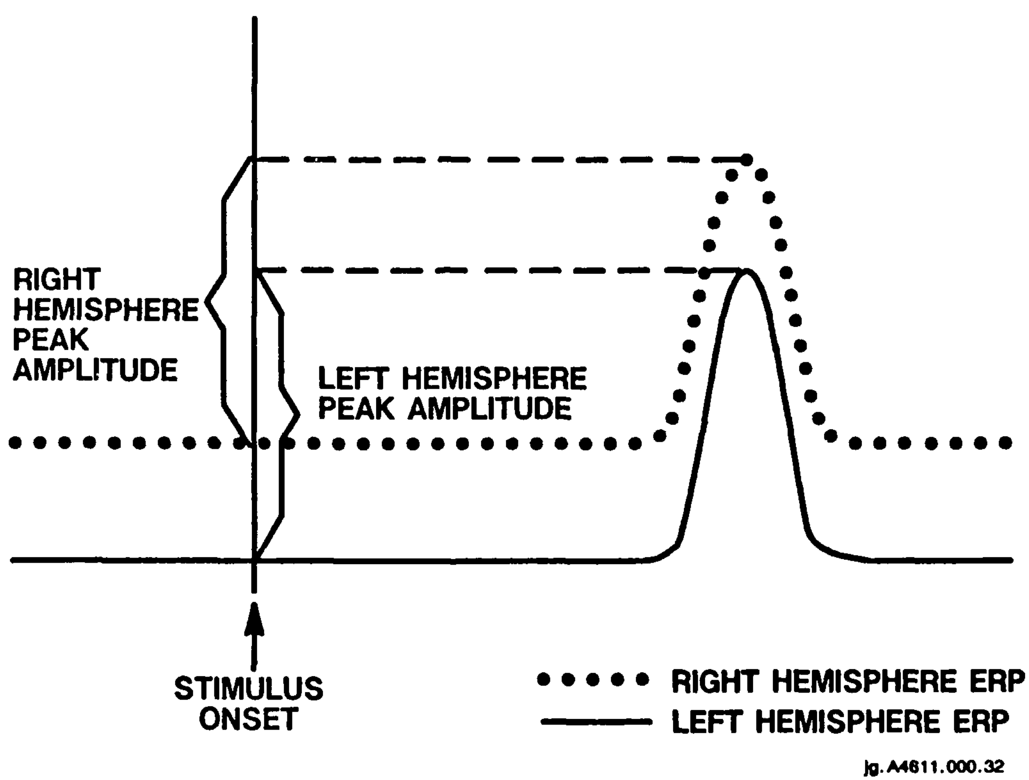

Figure 2. Measurement of P300 Peak Amplitude for each Hemisphere.

TABLE 12

ERP Analysis: Mean Peak Amplitude (volts) and Time (ms).

Peak Amplitude:

Recording Location-->		Central		Parietal	
Hemisphere-->		Left	Right	Left	Right
Handedness	Responding Hand				
Left	Left	30.74	39.77	37.65	50.77
	Right	29.52	35.36	33.98	42.44
Right	Left	32.90	46.72	44.22	52.27
	Right	31.68	33.44	37.25	39.26

Peak Time:

Recording Location-->		Central		Parietal	
Hemisphere-->		Left	Right	Left	Right
Handedness	Responding Hand				
Left	Left	797	797	811	799
	Right	797	800	782	785
Right	Left	776	781	834	833
	Right	798	790	803	800

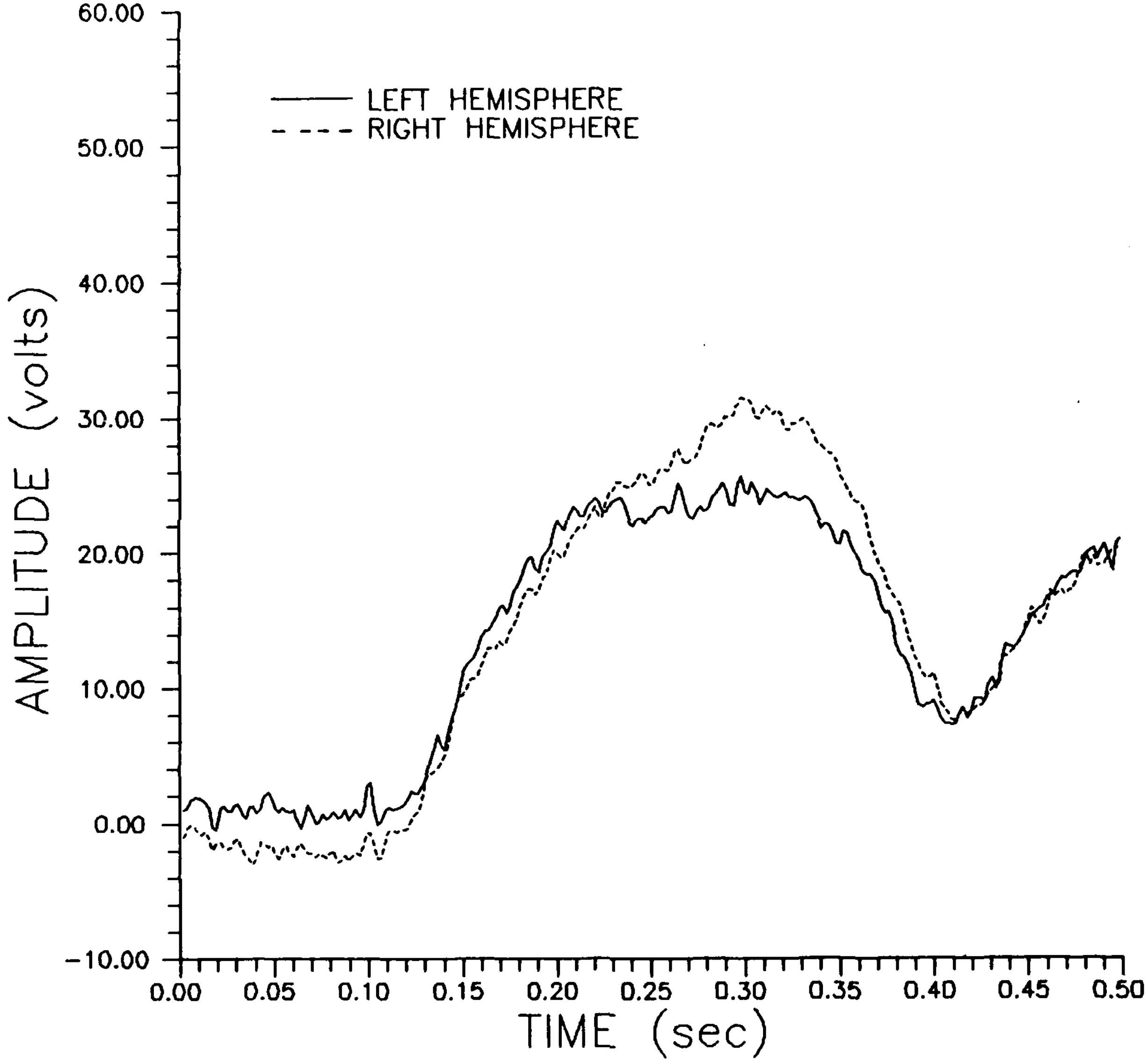

Figure 3. Right-handers' ERP: Central Location.

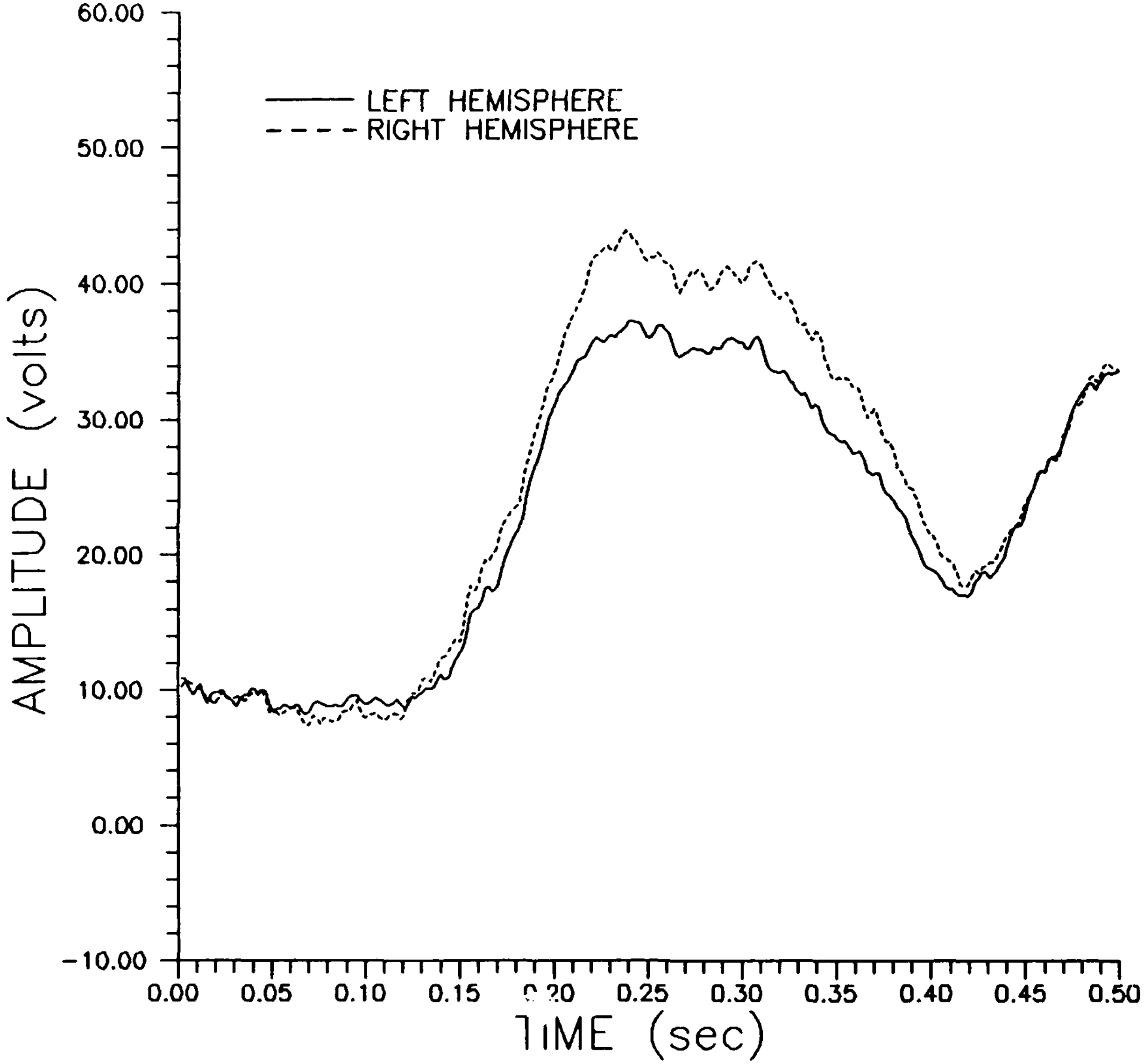

Figure 4. Left-handers' ERP: Central Location.

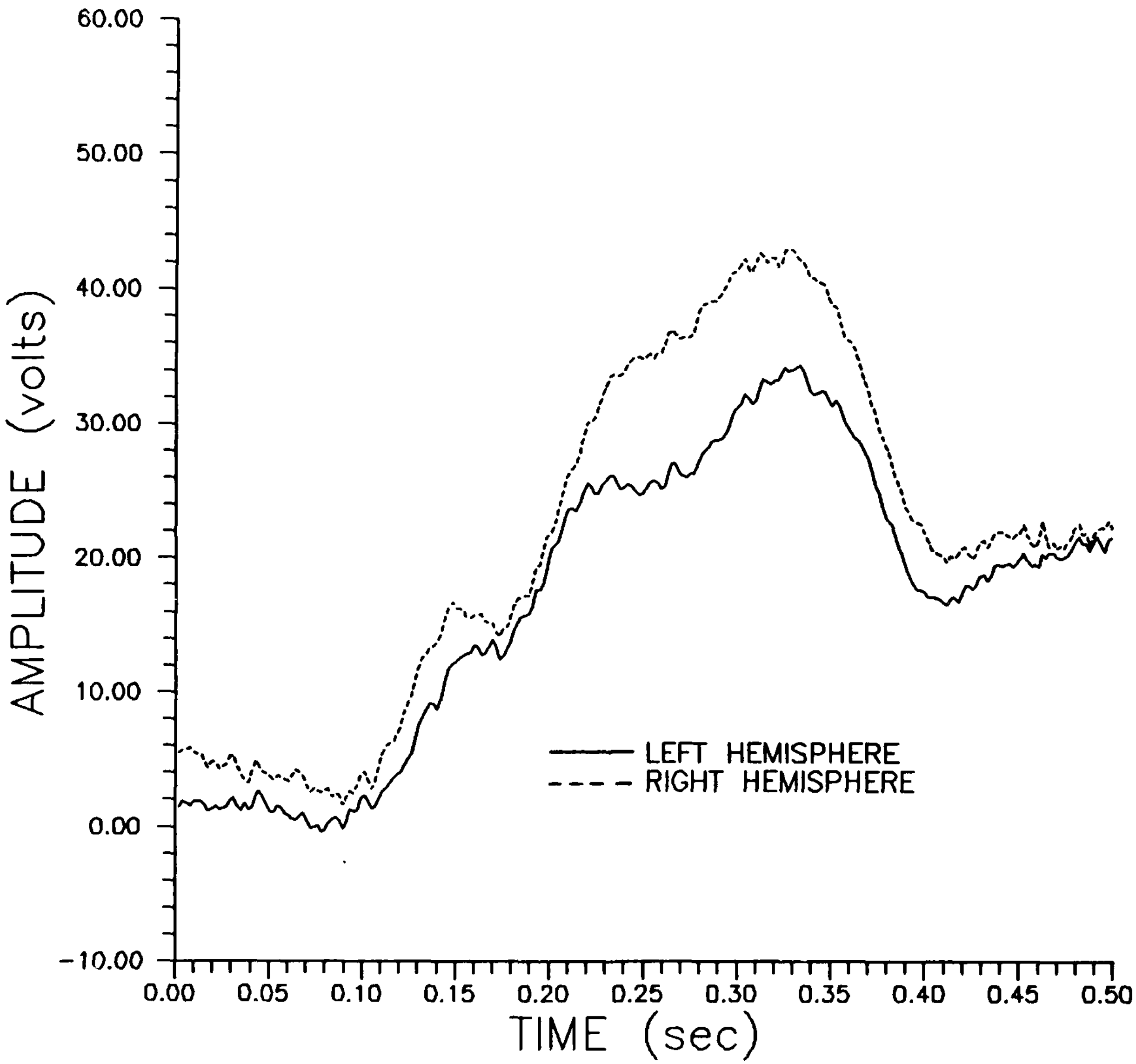

Figure 5. Right–handers' ERP: Parietal Location.

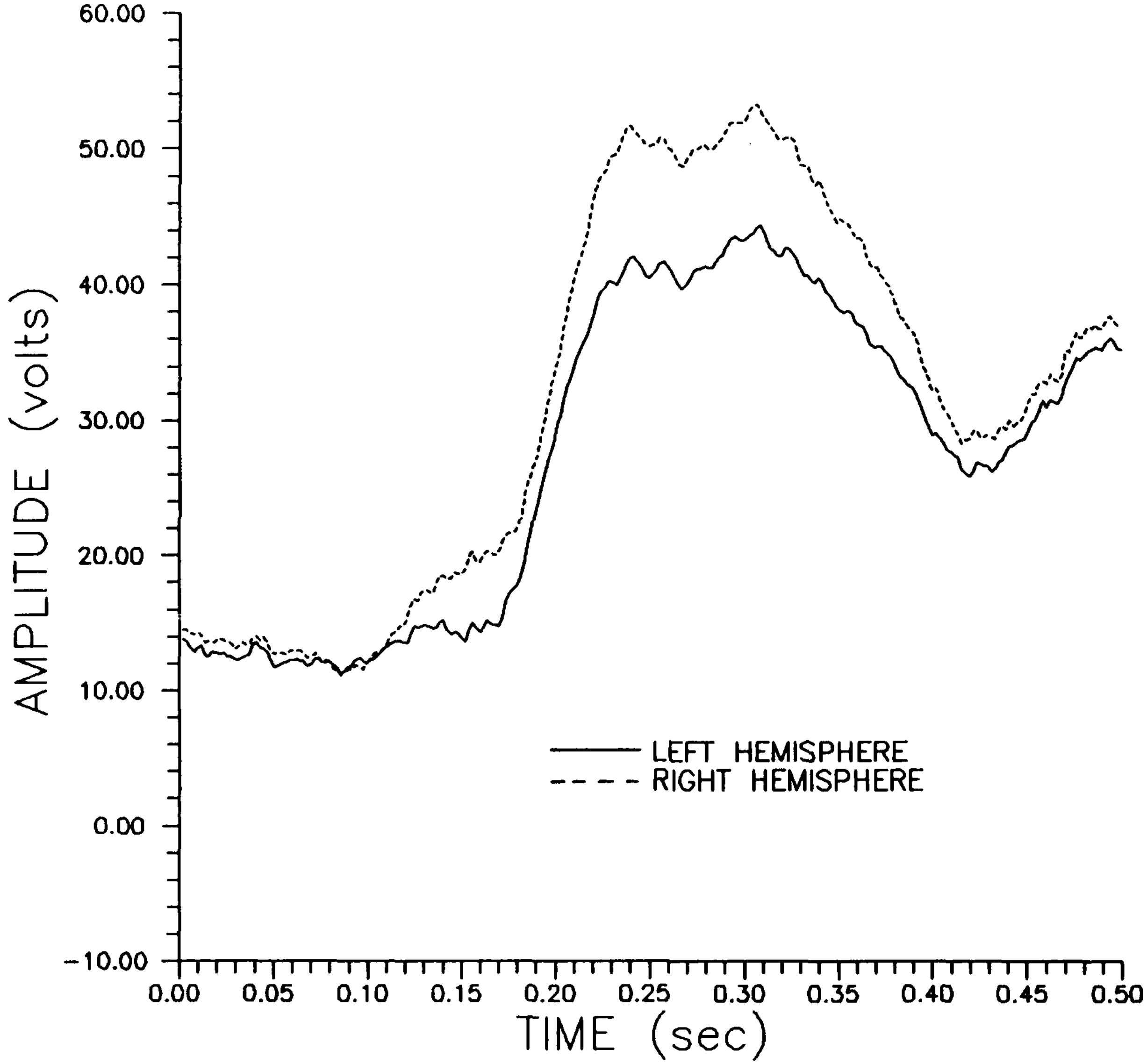

Figure 6. Left-handers' ERP: Parietal Location.

TABLE 13

ERP Peak Amplitude: Interaction Between Handedness, Hemisphere, and Recording Location

Recording Location-->	Central		Parietal	
Hemisphere-->	Left	Right	Left	Right
Handedness				
Left	30.13	37.57	35.82	46.61
Right	32.29	40.08	40.73	45.77

amplitude was similar for the two handedness groups. However, for the parietal location, this difference was greater for the left-handers than for the right-handers. At the parietal location, a greater difference between the handedness groups occurs at the left hemisphere location, as compared with the right hemisphere location.

There was also a near-significant interaction between hemisphere and responding hand ($F(1,34)=4.06$, $p<0.10$). As can be deduced from Table 12, the difference between the left and right hemisphere amplitude tended to be greater when left hand response was used, largely because the right hemisphere peak amplitude was very high with use of left hand response.

For the analysis of peak time, there was a main effect of location ($F(1,34)=4.39$, $p<0.05$), with the peak being earlier for the central location (792 ms) than for the parietal location (806 ms). There was a handedness by location interaction ($F(1,34)= 47.21$, $p<0.01$). At the central location, there was little difference between the peak time of the left-handers (798 ms) and that of the right-handers (786 ms). However, at the parietal location, the peak time of the left-handers (794 ms) was shorter than that of the right-handers (818 ms). There was also a responding hand by location interaction ($F(1,34)=7.03$, $p<0.01$). At the central location, there was little difference between the peak time when the left hand made the response to the lexical decision task (788 ms) and when the right hand responded (796 ms). However, at the parietal location, the peak time associated with right hand responding was shorter (793 ms) than that associated with left hand responding (819 ms).

To examine the within-group homogeneity of the ERP, the standard deviations of the voltages comprising the ERP as a function of time were computed within each handedness group and recording location. The standard deviations of these voltages over time are shown in Figures 7 through 10. The most notable feature in these figures is the large reduction in the between-subject variability of the left hemisphere potential of the right-handers at about the time of the peak amplitude. In contrast, for both hemispheres of the left-handers, there is an increase in between-subject variability between 200 and 400 ms post-stimulus, with a brief decrease in this general trend at about the time of the peak amplitude.

There was also evidence of a relationship between the absolute ERP amplitude and the level of post-stimulus alpha activity. Although there appeared to be no relationship between ERP amplitude and pre-stimulus alpha level, there were a number of significant relationships for the post-stimulus alpha level, shown in Table 14. In general, the greater the

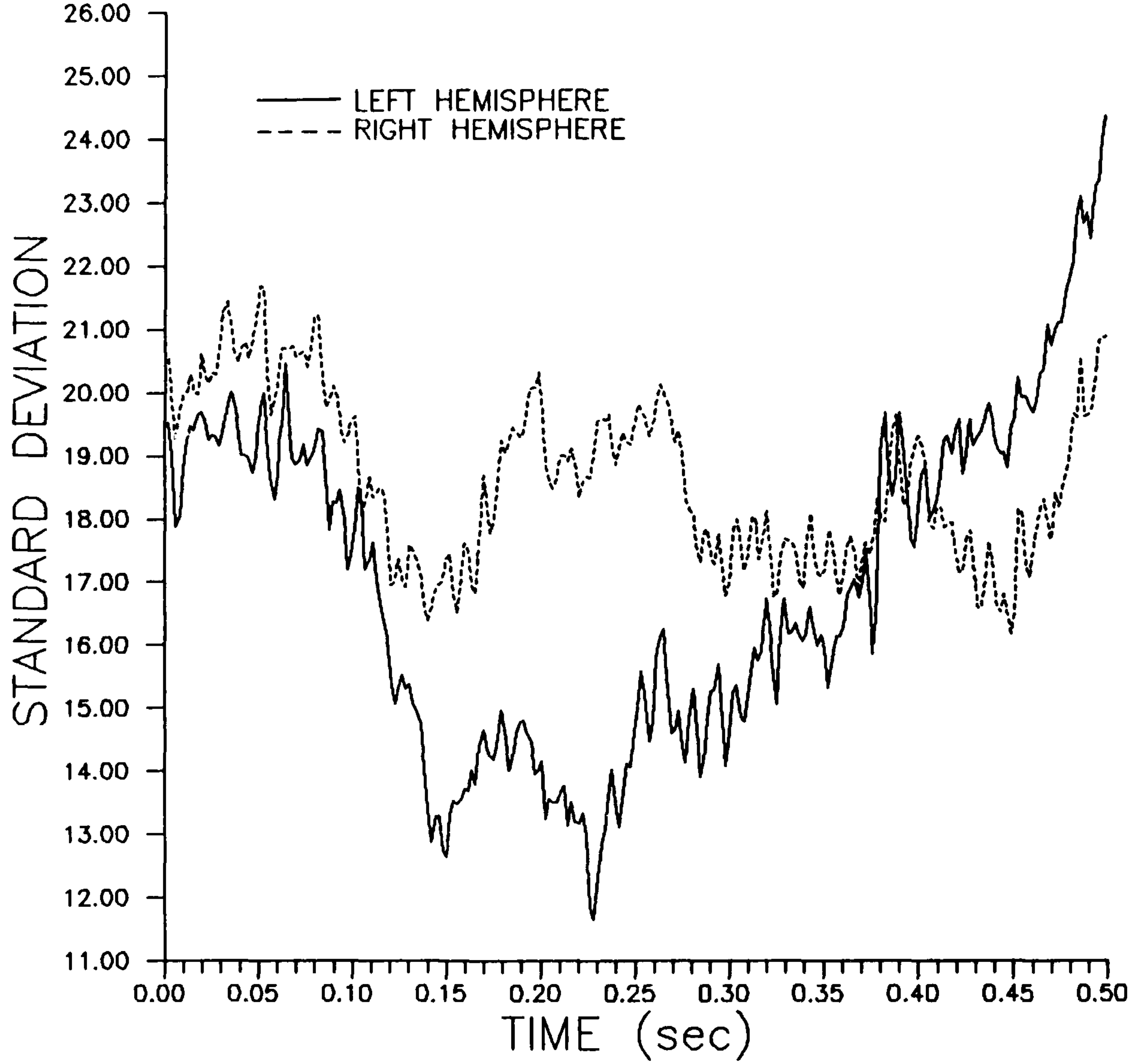

Figure 7. Standard Deviation of Right-handers' ERP: Central Location.

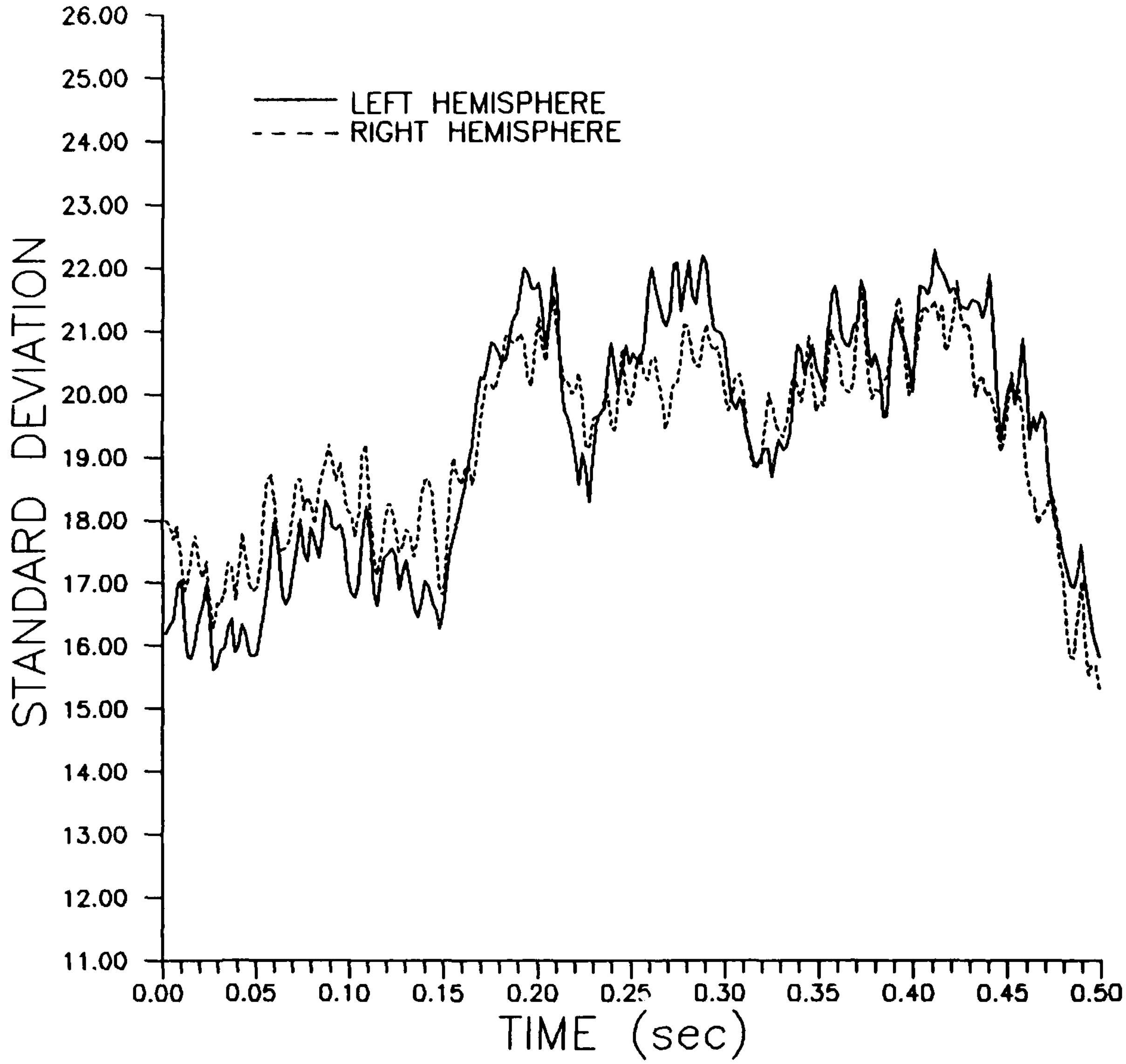

Figure 8. Standard Deviation of Left-handers' ERP: Central Location.

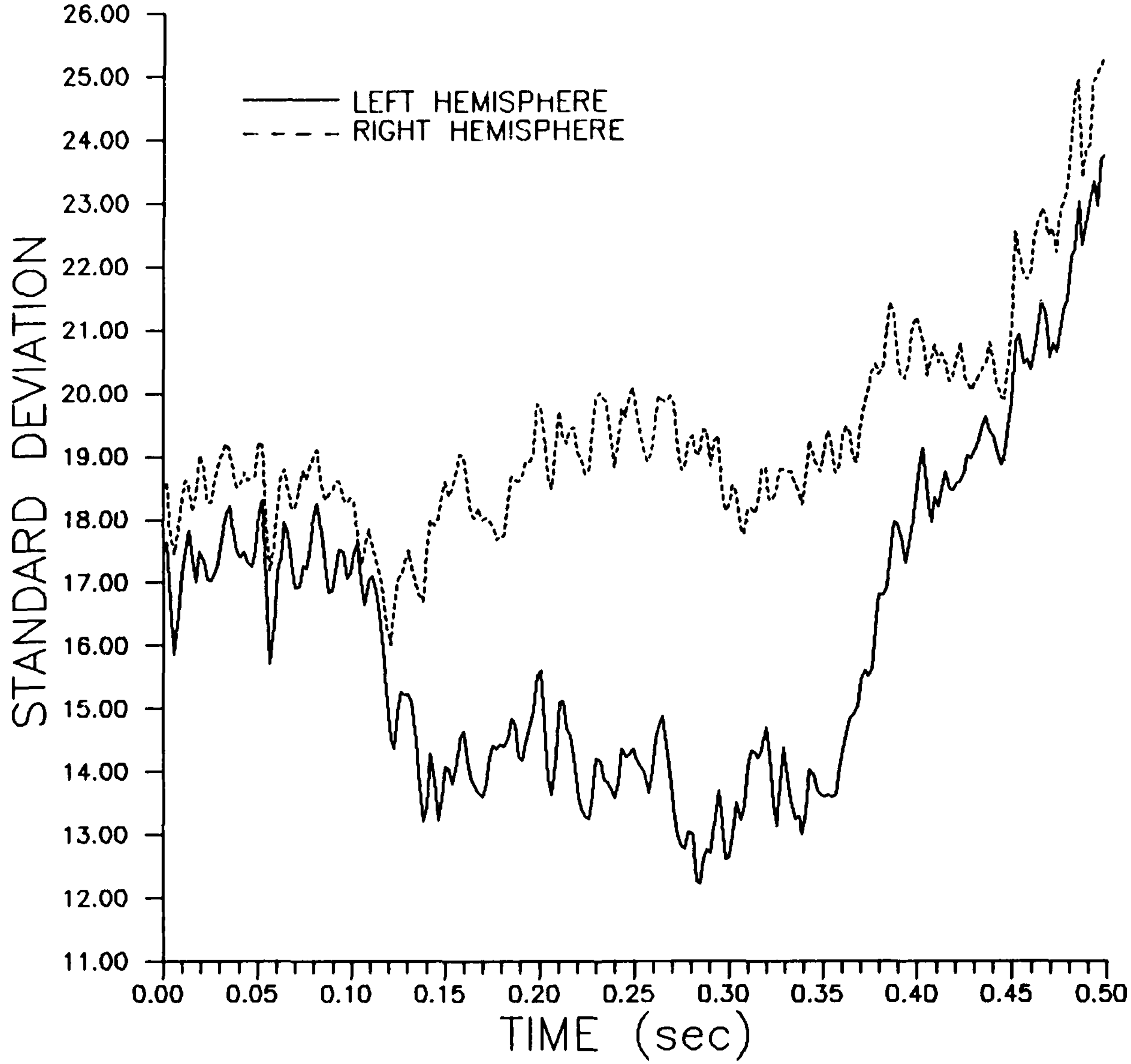

Figure 9. Standard Deviation of Right-handers' ERP: Parietal Location.

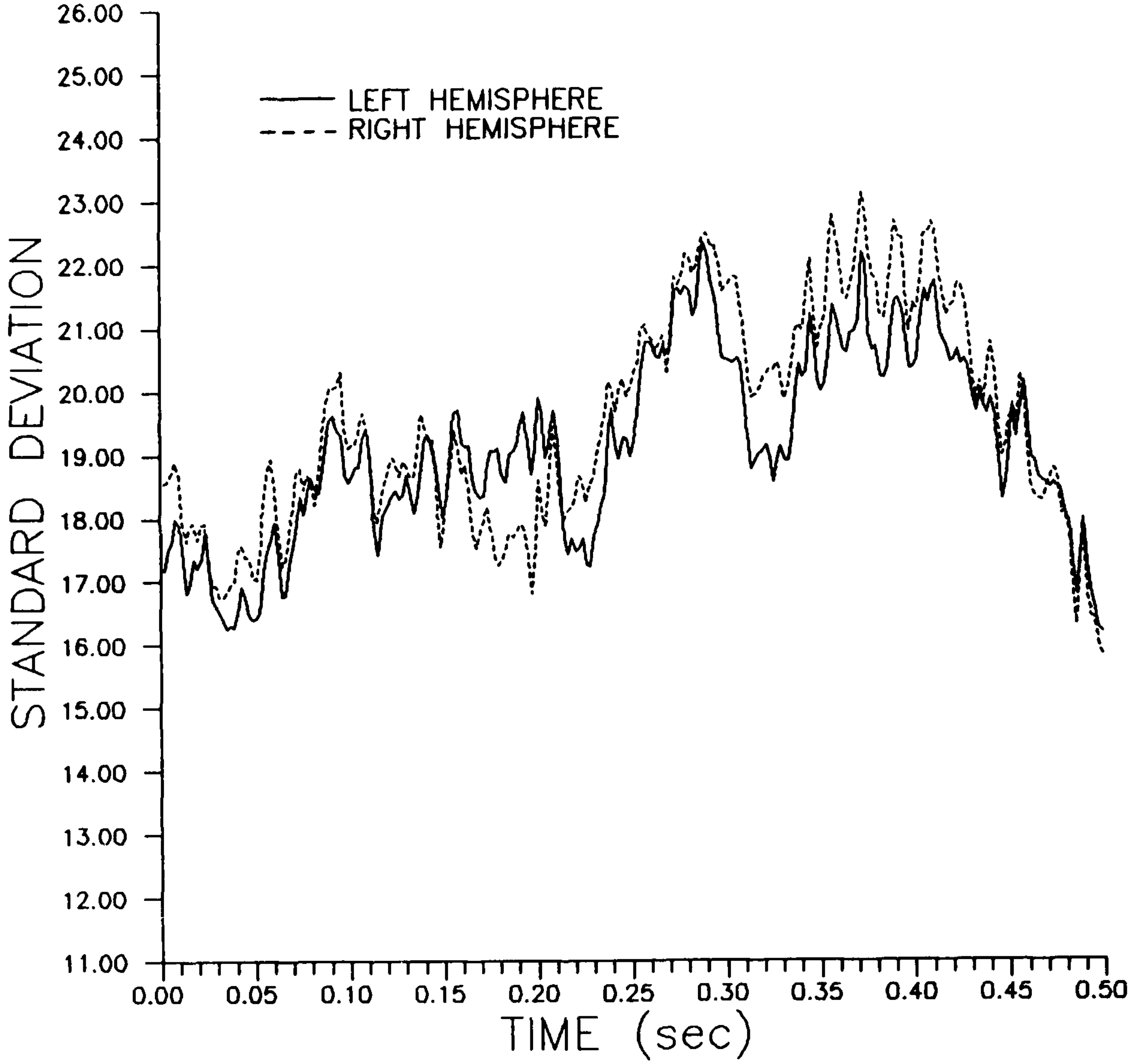

Figure 10. Standard Deviation of Left-handers' ERP: Parietal Location.

TABLE 14

Correlations Between ERP Peak Amplitude and Alpha Activity.

ERP Hemisphere	ERP Location	Alpha Activity Hemisphere	Alpha Activity Location	Time	Correlation
Left	Central	Left	Central	Post-stimulus	0.368*
		Right	Central	Post-stimulus	0.186
Right	Central	Left	Central	Post-stimulus	0.485**
		Right	Central	Post-stimulus	0.402*
Left	Parietal	Left	Parietal	Post-stimulus	0.414**
		Right	Parietal	Post-stimulus	0.360*
Right	Parietal	Left	Parietal	Post-stimulus	0.476**
		Right	Parietal	Post-stimulus	0.436**

* $p < 0.05$, 2-tailed
** $p < 0.01$, 2-tailed

level of post-stimulus alpha activity, the greater the ERP amplitude recorded at that location.

There was no relationship between the asymmetry in ERP amplitude and either perceptual asymmetry or alpha asymmetry.

4. Discussion of Results of ERP Analysis

The P300. In the present results, the most prominent feature of the ERP is a positive component appearing at 300 ms post-stimulus. As was mentioned earlier, the meaning of this P300 component and factors affecting it have been the subject of considerable research. Given the evidence of hemispheric and handedness group differences in aspects of the P300 in the present work, it seems appropriate to briefly review interpretations of the P300, particularly its potential applied value as a measure of processing workload.

One of the first paradigms in which the P300 was studied was the "oddball" paradigm, in which it was observed that the P300 was associated with the occurrence of rare, "target" stimuli, but not with more frequent nontarget stimuli (Sutton, Braren, Zubin, & John, 1965). Other studies have demonstrated that P300 amplitude increases as stimulus probability decreases (Johnson & Donchin, 1982), and that the amplitude decreases with practice (Rosler, 1981). It has been suggested that the P300 is related to attention-demanding processes such as the identification and classification of relevant stimuli (Hillyard & Picton, 1971) or the updating of the mental model about the stimulus environment (Donchin, Karis, Bashore, Coles, & Gratton, 1986).

Of greater interest for more applied purposes are recent studies suggesting that P300 amplitude is sensitive to changes in what can be conceptualized as perceptual-central "workload." One study demonstrating this sensitivity is by Israel, Wickens, Chesney, and Donchin (1980) using a task simulating the demands of air traffic control. Subjects performed one of two types of visual monitoring tasks -- a flash detection task in which increases in the intensity of certain stimuli were to be detected, and a course-change detection task in which changes in the movement of certain stimuli had to be detected. The difficulty of each of these tasks could be increased by increasing the number of stimulus elements on the display. Concurrent with one of the visual monitoring tasks, subjects performed one of two auditory tasks involving the monitoring of a series of tones for the occurrence of high-pitched (target) tones. The results indicated that the amplitude of the P300 to the target tones was inversely related to the difficulty of the visual detection task. P300 amplitude was highest when an auditory task was performed alone, and was lowest when the visual task

involved the monitoring of the greatest number of stimuli. In other words, as the difficulty of the visual monitoring task increased, the amplitude of the P300 decreased.

This study is of particular interest because it indicates that the difficulty of a fairly complex and demanding task can be monitored by recording the ERPs elicited by a simple, relatively unobtrusive stimulus. The relationship between P300 amplitude and workload has been demonstrated using a variety of task combinations and manipulations of task difficulty (Israel,Chesney, Wickens, & Donchin, 1980; Kramer, Wickens, Vanasse, Heffley, & Donchin, 1981). Manipulations of factors affecting perceptual-central processing versus response selection or execution indicate that P300 is selectively sensitive to perceptual-central processing difficulty.

Hemispheric and Handedness Group Differences in P300. In the present work, the analysis of P300 amplitude provides evidence of hemispheric functional asymmetry. The P300 amplitude was lower for the left hemisphere than for the right hemisphere. The meaning of the lower left hemisphere amplitude is clarified by consideration of the relationship between the P300 amplitude and the level of alpha activity. The P300 amplitude was directly related to the level of post-stimulus alpha activity, suggesting that as brain activation increased, the P300 amplitude decreased. Assuming that increases in brain activation are related to increases in workload, the results suggest that, in the present paradigm, P300 amplitude decreased as workload increased. In other words, P300 amplitude was inversely related to workload. It appears that, although the present paradigm involves only a single task (lexical decision-making), the relationship between P300 amplitude and workload is similar to that observed in the dual-task paradigms previously discussed.

The inverse relationship between P300 amplitude and workload suggests that the difference in the left and right hemisphere amplitudes reflects the fact that left hemisphere workload was greater than right hemisphere workload. This is consistent with the importance of the left hemisphere in lexical decision-making.

Although there was no overall handedness group differences in the asymmetry of the P300 when central and parietal data were collapsed, there was some evidence of difference for ERPs recorded at the parietal location alone. There appear to be handedness group differences in the amplitude of the P300 recorded over the left parietal location. For the left parietal location, the left-handers had a lower P300 amplitude than did the right-handers. This difference did not appear for the right parietal location.

The data suggest that the processing demands of the lexical decision task were more taxing for the left hemisphere of the left-handers than for the left hemisphere of the right-handers. There were no handedness group differences in right hemisphere processing.

The latter result is inconsistent with the idea that among left-handers, the right hemisphere is more frequently involved in language-related processing. The results of the EEG spectral analysis support the notion that activation was more asymmetrical for the right-handers than for the left-handers. The ERP analysis does not, however, support this variation in the asymmetry of activation. In fact, at the parietal location, at which handedness group differences were observed, the left-handers were, if anything, more asymmetrical in P300 amplitude than were the right-handers.

In addition to handedness group differences in the P300 amplitude, other aspects of the data also provided evidence of group differences in brain functioning. There was evidence of group differences in the P300 parietal peak time, with the left-handers exhibiting an earlier peak time. The meaning of this difference is unclear. More interesting were hemisphere-specific handedness group differences in the within-group homogeneity of the ERP. In particular, the reduction in the between-subject variability of the right-handers' left hemisphere ERPs at the time of the P300 is consistent with the idea that right-handers' brain functioning, especially left hemisphere functioning, is more homogeneous that is that of left-handers. Assuming a relationship between P300 and some aspect of attentional processing, the between-subject similarity in the ERP at 300 ms post-stimulus suggests that at that time, some aspect of attentional activity occurs fairly uniformly within right-handers and is heavily associated with left hemisphere processing, at least for the lexical decision task. The fact that the left and right hemispheres exhibited different ERP patterns supports the notion that the hemispheres represent, at least to some extent, independent attentional systems.

SECTION VI

CONCLUSIONS AND FUTURE DIRECTIONS

A. Conclusions

The long-term goal of the present program is to apply knowledge of brain functioning, particularly individual differences in brain functioning, to system design in order to improve human performance. During this first year of the program, the research has focused on examining the nature of individual differences in brain functioning, and on identifying measures which might be used to assess such differences. The research has focused on comparisons of left-handers and right-handers, since these groups are known to vary in brain functioning in certain important respects.

The results provide clear indication that a variety of measures reflect evidence of handedness group differences that are related to differences in brain functioning. First, gross behavioral measures of motor dominance provide evidence of handedness group differences. In contrast, finer measures of performance (i.e., reaction time), while providing evidence of hemispheric functional specialization, are not sensitive to handedness group differences in specialization.

Electrophysiological measures were, in general, very sensitive to individual differences in brain functioning. Spectral analysis of ongoing electroencephalographic (EEG) activity, particularly of alpha (8-12 Hz) activity, revealed handedness group differences in both conditions in which differences in brain functioning have been hypothesized. The nature of the alpha differences was consistent with the nature of the differences in brain organization that have been described by others, i.e., evidence of greater heterogenity of language lateralization among left-handers than among right-handers.

Analysis of event-related potentials (ERPs) also provided evidence of handedness group differences and, perhaps, more significantly, of the potential usefulness of certain components of the ERP for assessing workload, including individual differences in workload. As was discussed in Section V, there is a variety of evidence suggesting that the amplitude of the P300 component reflects the level of perceptual-central workload experienced by the operator. In the present work, the amplitude of the P300 was sensitive to hemispheric differences and to handedness group differences. This result suggests that the P300 might be usefully applied in assessing individual differences in certain aspects of performance.

B. Future Directions for the Research

During the course of the past year, feedback from A.R.I. has encouraged more careful consideration of how the present research can contribute to system design, particularly the design of adaptive systems. In considering this, two related issues have emerged. The first reflects the initial motivation for the research, that is, what are the consequences of individual differences in brain functioning for human performance? The results of this year's work have posed a related and very interesting, second issue -- how can the measurement of parameters of brain functioning, including individual differences in brain functioning, be usefully applied to improving the measurement of human performance and to the design and performance of human-machine systems?

One major challenge for the designers of complex human-machine systems is the development of procedures for measuring operator workload and for minimizing conditions in which the operator is overloaded such that system performance suffers. The importance of measuring workload in adaptive systems will be considered here. One advantage of adaptive systems is that they adjust the nature of the task/information imposed on the operator based on estimates of his current workload. A key factor in making good decisions regarding modifications of the operator's task loading is the capability of the system to estimate the current workload of the operator and to predict the impact upon overall performance of adding another task to the operator's load. Preferably, in estimating workload and in predicting the effects of changes in workload, such a system should be able to adapt to individual differences among operators and to the differential impacts of various changes in tasks/information. For example, different individuals may have different workload capacities, and these must be considered in deciding whether changes in tasks/information should occur.

Given the importance of measuring workload in such systems, it is planned that one future focus of the current research program will be on investigating how measures of brain functioning, including individual differences, can contribute to the measurement of workload in adaptive systems. Although a variety of approaches to the measurement of workload have been explored, each of these has significant problems for use in complex, demanding, human-machine systems. For example, subjective measures, i.e., requiring the operator to estimate his workload and capability to take on additional tasks, imposes an additional decision on the operator and has the effect of increasing his workload. Performance measures of workload are problematic in that performance does not degrade gracefully, that is, performance may degrade gradually

as workload is increased up to capacity, at which time there is a drastic change in the quality of performance. It is obviously not practical to use such drastic changes as indicators of when the operator's workload limit has been reached.

There are several rationales for arguing that electrophysiological measures may be useful in measuring operator workload. First, there is a variety of evidence indicating that the P300 of the ERP has great potential as a measure of perceptual-central workload. Measurement of the ERP can be included in complex systems in a relatively unobtrusive fashion without imposing significant, additional workload on the operator. Second, since electrophysiological measures are sensitive to individual differences in brain functioning, their use would provide evidence about how such differences impact performance, in particular, the workload experienced by an individual operator. This would allow better decisions to be made about the significance of individual differences in brain functioning, and the importance of including measurement of these.

It is therefore planned that one focus of the future research will be to contribute to the performance of human-machine systems by developing several psychometric models that can be applied to the assessment and prediction of operator workload. An important focus of the work will be exploration of the value of electrophysiological measures for estimating workload. The research will involve two phases. During the first phase, a psychometric measurement procedure which assesses critical individual characteristics and allows specification of individual operator profiles will be developed. During the second phase, a psychometric prediction model which uses this profile to predict workload level will be developed. One focus of the work during the next year will be on the identification of the necessary profile components and of algorithms that can be used in a predictive model.

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APPENDIX A

A Review and Assessment of Spectral Estimation Techniques

for

Short Data Record Length EEG Data Analysis

A Introduction

This appendix will present the results of a study which sought to answer the question "Given a short record of sampled EEG data (say 1/4 of a second), how does one best estimate the power spectrum of that signal?". There are two primary approaches to the problem -- classical Discrete Fourier Transform (DFT) methods, and modern model-based methods. In this Appendix, a more complete description of the problem of spectral estimation will first be provided. Next, the philosophical differences between the modern and classical methods will be presented. This will be followed by an in-depth look at the details of different modern methods -- in particular to the application of these spectral estimation techniques to the analysis of EEG data. The appendix concludes with some actual experimental results that show the performance of a specific (autoregressive least squares) modern method as compared to the classical DFT approach.

1 The Spectrum

The spectrum, or power spectrum, of a signal is the curve, graph, or function that specifies the frequency content of a time domain signal. A pure sinusoid, for example, has a spectrum consisting of a single line -- all of the signal power is concentrated at the frequency of the signal. It turns out that any periodic signal can be expressed in terms of a summation of harmonically related sinusoids. That is to say, for example, an infinite duration square wave has a power spectrum that consists of a series of vertical lines. Other signals have spectra that are specified by smooth curves rather than discrete lines. In general, any signal that is time-limited will have a continuous spectra.

There are two fundamental types of signals discussed in this appendix -- random and deterministic. Deterministic signals are those with no random components. For example, the signal

$$s(t) = \sin(2\pi f t) \tag{1}$$

is a deterministic signal. Random signals possess a random term which may not be written down uniquely. These signals are usually defined in terms of their statistical properties, but nonetheless, they, too, have power spectra.

For deterministic signals, the power spectrum is defined to be the square of the magnitude of the Fourier transform of the signal. For random signals, the power spectrum is defined to be the Fourier transform of the signal's autocorrelation function.

Since autocorrelation involves expectation, the power spectrum of a sampled random signal may not, in general, be precisely computed. Only if many sequences, or long time samples, are available may the spectrum be confidently calculated. All this aside, it is often of interest to know the spectra of a random signal when the only data available are several short records. The approach most often taken is to ignore the fact that the signals are random, and simply transform the data to get an approximation to the true spectrum.

As mentioned above, there are two primary methods used for transforming sampled data, the modern approach and the classical approach. The classical approach is to simply perform the discrete version of the Fourier transform of the data to yield the spectral estimate. The modern, model-based approach, is a bit more complicated.

To understand the concept of model-based spectrum estimators, it is very helpful to think in terms of filters. Imagine that the input to a filter is white noise. Since white noise has equal power at all frequencies, its power spectrum is simply a horizontal line. Now, suppose that this input is passed through a lowpass filter. The spectrum of the signal that comes out of the filter will have more energy at the low end of the spectrum than at the high end, and its shape will be equal to the transfer function of the lowpass filter. Since filter transfer functions may be made to look like almost anything, it is reasonable to think of this as a method for performing spectrum estimation. This is exactly how modern model-based methods work. They attempt to find the transfer function that best matches the spectrum of the data. Because these techniques update their transfer function estimates with each new data point, they are often referred to as adaptive.

Although all of the modern methods described in this appendix operate using the philosophical model described above, they all use different methods for calculating the filter transfer function. Because of this, they may produce considerably different results.

B <u>Review of Spectral Estimation Techniques</u>

In this section, the advantages and disadvantages of both the modern and classical spectral estimation methods will be discussed. It is very important to keep in mind when reading the following discussion that differences between the spectral estimates produced by the Fourier method and those produced by the modern methods can be traced back to the generating process, or model, which each method assumes to have produced the signal.

1 Fourier Techniques

The model assumed when using the Fourier approach is that the signal was generated by the sum of an infinite number of sinusoids. However, the Fourier approach (like the modern methods) is usually implemented on discrete, quantized samples of a data record. This means that instead of calculating the Fourier Transform, the Discrete Fourier Transform (DFT) must be calculated. The use of the DFT changes the model, and the signal is now assumed to have been generated by a finite sum of harmonically related sinusoids. The DFT calculates the amplitude and phase associated with each sinusoidal component. The power spectral estimate is then calculated by squaring the magnitude of each sinusoidal component.

2 Modern Model Based Methods

The modern methods which will be discussed assume a completely different model of the signal generator. The modern methods assume the current data sample is produced by the sum of weighted past data samples and weighted random inputs:

$$y(n) = -\sum_{i=1}^{p} a(i)y(n-i) + x(n) + \sum_{i=1}^{q} b(i)x(n-i) \qquad (2)$$

where : $y(n)$ = output at time n
$x(n)$ = random input at time n
$a(j)$ = autoregressive coefficient j
$b(j)$ = moving average coefficient j

The sum of p and q is referred to as the model order. The difference between the modern methods is in how the coefficients are calculated. Once the coefficients have been selected, the spectrum is computed by taking the z-transform (Oppenheim & Schafer, 1975) of the above equation. The result is:

$$S(f) = \frac{\sigma^2 \Delta t \,|\sum_{k=1}^{q} b(k)\exp(-j2\pi k f \Delta t)|^2}{|1 + \sum_{k=1}^{p} a(k)\exp(-j2\pi k f \Delta t)|^2} \qquad (3)$$

where: $j = \sqrt{-1}$
Δt = time between data samples
σ^2 = mean power output of the model
f = frequency in Hertz

The modern methods which will be discussed can all be categorized as autoregressive moving average (ARMA) techniques. However, the designation of ARMA is usually reserved for those models where at least one autoregressive coefficient is non-zero

and at least one moving average coefficient is non-zero. If all of the moving average coefficients are set equal to zero, then the model is termed an autoregressive (AR) model. The different types of AR models which will be discussed are the Yule-Walker (YW) model, the Kalman filtering approach, and the generalized least squares (LS) approach. A special case of the LS approach which will be discussed is called the Burg method.

As mentioned above, the AR approach differs from the ARMA approach in that all moving average coefficients are set equal to zero. This means that the AR model has only poles (zeros in the denominator polynomial) in the rational equation defining the spectrum whereas the ARMA method has poles and zeros (zeros in the numerator polynomial). The difference between the ARMA and AR models in the time domain can be explained in terms of how the signal is assumed to have been generated. The AR model assumes the signal is a linear regression only of itself, and that $x(t)$ represents the error of the model. The ARMA model assumes the signal is a linear regression of itself plus a linear regression of past errors and $x(t)$ represents the present error of the model. The AR method is related to the ARMA model by the Wold decomposition theorem (Witman, 1974, referenced in Kay & Marple, 1981). This theorem states that any stationary ARMA process (an ARMA process whose statistics do not change with time) of finite variance can be represented by a unique AR model of possibly infinite order. Therefore, if an AR model is chosen to represent an ARMA process, a good approximation may be obtained by making the order of the AR model large.

When using the AR approach to spectral estimation, the Moving Average (MA) coefficients are all set to zero and only the AR coefficients need to be calculated. The calculation of the AR coefficients is very similar to linear prediction theory (Kay & Marple, 1981). If a present output is predicted on the basis of p previous outputs:

$$\hat{y}(n) = \sum_{j=1}^{p} a(j)y(n-j) \tag{4}$$

then the AR coefficients can be chosen to minimize the mean squared error:

$$E\{|y(n)-\hat{y}(n)|^2\} \tag{5}$$

where: $E\{\cdot\}$ denotes the expected value operation.

The above error is known as the forward prediction error. If an output is predicted on the basis of p future values:

$$\hat{y}(n) = \sum_{j=1}^{p} a(j)y(n+j) \tag{6}$$

then, once again, the AR coefficients can be chosen to minimize the mean squared error:

$$E\{|y(n) - \hat{y}(n)|^2\} \tag{7}$$

In this case the error is called the backward prediction error.

Since all modern methods require selection of the model order, a few words are in order concerning its selection. The process of selecting the model order for an ARMA process, or equivalently selecting p and q in equation 2, is a topic of great importance since different model orders may produce radically different spectral estimates. Much research has been performed on the topic; however, no absolute solution exists.

The general procedure for estimating model order is to first select p and then calculate the AR coefficients. The data are then filtered using the AR coefficients to produce a MA process. The order and the MA coefficients are then found for this MA process (Kay & Marple, 1981). Selection of the model order p for AR models has received the most attention. The methods which will be described in this Appendix monitor the prediction error as the model order is increased. The prediction error for all these methods decrease monotonically with increasing model order, so it is not possible to look for a minimum in the prediction error. Alternately, researchers have developed functions of the prediction error which do yield minima.

Gersch (1970) has used a method where for each increase in model order a statistic k is calculated:

$$k = \frac{v(p-1) - v(p)}{v(p)} \tag{8}$$

where: $v(j)$ = prediction error for model order j

The statistic k is calculated for each increasing model order. When k becomes less than a chosen value, the current value of p is selected as the model order.

Akaike has suggested two other techniques to choose the model order (Akaike, 1970, 1972, referenced in Kay & Marple, 1981). The first technique is called the final prediction error (FPE) and is given by:

$$FPE = v(p)\frac{N+p+1}{N-p-1} \tag{9}$$

where: N = number of data samples

The FPE is calculated for increasing p until a minimum is found. This value of p is then used as the model order.

Another technique presented by Akaike is the Akaike information criterion (AIC). The AIC is calculated using:

$$AIC = \frac{\ln(\upsilon(p)) + 2(p+1)}{N} \tag{10}$$

As with the FPE, the AIC is calculated for increasing p until a minimum is found and that value of p is used for the model order.

Parzen has suggested another method of AR model order selection (Parzen, 1974, as referenced in Kay & Marple, 1981). It is called the criterion autoregressive transfer (CAT) function and is calculated by:

$$CAT = \left(\frac{1}{N}\sum_{j=1}^{p}\frac{1}{\upsilon(j)}\right) - \frac{1}{\upsilon(p)} \tag{11}$$

Once again the CAT is calculated for increasing p until a minimum is found and that value of p is used as the model order. Despite all of the methods developed to choose the model order p, many cases have been found where these methods do not work well. This has been reported to be especially true for short records of actual (not simulated) data (Kay & Marple, 1981).

In the following subsections, the Burg, Yule Walker, Kalman, and Least Squares algorithms will be specifically addressed, to reveal the subtle differences in the underlying assumptions used in the development of each of the algorithms.

a <u>The Yule Walker (YW) Technique</u>

The YW approach minimizes only the forward prediction error. However, when this is done the equations which result to calculate the AR coefficients require calculation of the autocorrelation lags. When the autocorrelation lags are calculated, the data outside the interval being analyzed is assumed to be zero. This implies that the data has been windowed (as in the Fourier approach) and sidelobes are generated.

b <u>The Generalized Least Squares (LS) Method</u>

The LS method minimizes the sum of the forward and backward prediction errors. The equations which result to calculate the AR coefficients use only the data in the interval being analyzed.

No assumptions about data outside the interval are made and thus there is no implied windowing. Therefore no sidelobes will be generated and better spectral resolution can be expected.

c The Burg Recursion

The Burg method of spectral estimation is a special case of the generalized least squares method. The Burg method imposes the constraint that the AR coefficients must satisfy the assumptions of the Levinson recursion algorithm (Kay & Marple, 1981). This constraint guarantees that the model produced will be stable. The constraint placed by the Burg method also leads to two disadvantages. First, bias is introduced in the frequency estimates. Second, spectral line splitting can occur (Kay & Marple, 1981). Spectral line splitting happens when a sinusoidal peak in the frequency domain splits into two peaks, each close in frequency to the actual frequency. The LS approach does not suffer from these disadvantages, but does have the disadvantage of not always producing a stable model. The LS method is generally thought to produce a better spectral estimate than the Burg method.

d Kalman Filtering

The Kalman filtering approach provides a method of dealing with time-varying AR coefficients. The AR coefficients are updated with each new data sample and in this way the AR method can be made to adapt to a signal which is not stationary.

3 Comparison of Modern and Fourier Techniques

In this section, a comparison of the FFT and modern spectral estimation techniques will be presented. Particular attention is directed toward the advantages of the modern methods over the classical approaches. In part a and b of this section, general pros and cons of the modern methods over the FFT-based approaches are presented, while part c presents the particular advantages for short data record length EEG data analysis.

a Advantages and Disadvantages of Modern Spectral Estimation Techniques

Perhaps the most advantageous characteristic of the modern methods is that they have better frequency resolution, especially for short data segments (Kay & Marple, 1981; Marple, 1978). Frequency resolution is the ability to discriminate two sinusoids which are closely spaced in frequency. If frequency resolution is poor, two closely spaced sinusoids may appear as one sinusoidal component. Another advantage of the modern methods (except for the YW method) is that there is no implied windowing as in the Fourier approach. Because there is no explicit

windowing, the sidelobe leakage problem of the FFT approach is not present. This is very important when trying to identify a low level signal which is close in frequency to a high level signal. The modern methods also have shown better performance in detecting small movements in the frequency of peaks (Jansen, Bourne, & Ward, 1971). The origin of this advantage can be attributed to the difference between the assumed signal models of the Fourier and modern methods. The Fourier model assumes that the signal may be represented by a sum of harmonically related sinusoids. The modern methods do not place a constraint on the frequency of sinusoidal components and therefore tend to give better frequency estimates. Further, they are better able to detect small changes in frequency location. A final advantage of the modern techniques is data reduction. The Fourier method requires approximately N/2 (N = number of EEG data samples) data points to describe the spectrum whereas the number of data points required by the modern methods is equal to the number of coefficients in the model.

The modern methods of spectral estimation also have disadvantages. As mentioned above, the LS method can result in unstable models. However, the generation of unstable models using the LS approach is reported to be very rare. For example, Marple (1980) processed over three thousand actual data segments using the LS method and found less than 1 percent of the models to be unstable. Nuttall, 1976 (as referenced in Marple, 1980) processed narrowband signals and found no unstable models. Even when unstable models are generated, it is of little concern from the standpoint of spectral estimation (Marple, 1980). (Filter synthesis, for example, mandates stable models.) Another disadvantage which has been mentioned is that spectral line splitting can occur. Line splitting occurs in the YW and Burg methods but not in the LS method. Perhaps the biggest disadvantage of the modern methods is that the order of the model must be selected. This means that appropriate values of p and q must be selected for ARMA models and an appropriate value of p must be selected for AR models. The order selected is very important to the spectral estimate. If the order of the model selected is too small then the spectral estimate will be too smooth; peaks will not be sharp enough, and spectral resolution will be lost. If the order selected is too large then the spectral estimate will be very bumpy and spurious peaks will be produced.

b <u>Advantages and Disadvantages of FFT-Based Spectral Estimation Techniques</u>

One advantage of the Fourier method is that many algorithms have been developed to efficiently calculate the DFT. An algorithm called the Fast Fourier Transform (FFT) (Cooley &

Tukey, 1965) has become quite popular although more efficient algorithms have recently been developed (Burrus & Eschenbacher, 1981; Sorensen, Heideman, & Burrus, 1986). Because the DFT can be rapidly calculated, the Fourier approach is very useful in real-time applications where computational speed is a limiting factor. Computational efficiency is also an advantage if large data segments are to be analyzed. Another advantage of the Fourier approach is that the power spectral density estimate is directly proportional to the power in the signal for sinusoidal processes (Kay & Marple, 1981). The Fourier approach also does not have stability problems which occur in some of the modern methods.

Despite the advantages of the Fourier approach, it suffers from many disadvantages, especially for short data records. First, the frequency resolution of the Fourier approach is inversely proportional to the observation interval. This means that for short data records the Fourier method will have poor frequency resolution and two sinusiods which are close in frequency may not be resolvable. Another disadvantage of the Fourier approach is produced because the DFT is only calculated over a finite number of data points. Data outside the time interval over which the DFT is calculated are assumed to be zero. The original time domain signal has in effect been multiplied by a rectangular window of width equal to the observation time of the data. This multiplication of the time domain signal corresponds to a convolution in the frequency domain. The convolution operation smears the spectrum and produces sidelobes. Sidelobes are a problem because the sidelobes of a strong signal can hide the mainlobe of a low level signal. The rectangular window has the narrowest mainlobe in the frequency domain but also has a very high first sidelobe level only 13 dB below the mainlobe. If the data are multiplied by a window function other than the rectangular (i.e. the Hamming or Taylor window) before the DFT is calculated, then lower sidelobe levels can be obtained but at the expense of a wider mainlobe. For a complete discussion of window functions see Harris, 1978. Another disadvantage of using the Fourier approach is that the variance of the spectral estimate does not decrease as the number of data samples increases. To obtain a consistent estimator, many spectral estimates must be averaged together (Welch, 1967).

c <u>Application of Spectral Estimation Techniques to EEG Data</u>

Much current research involves the application of spectral analysis to EEG signals. The 0 - 16 Hz range is usually the only part of the spectrum that is analyzed. It is (somewhat arbitrarily) divided into four regions called delta (0 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 12 Hz), and beta (12 - 16 Hz). EEG spectral analysis has been used to analyze both evoked and

spontaneous activity (Fenwick, Michie, Dollimore & Fenton, 1971; Heinze, Kunkel & Massing, 1981). Also, many researchers have investigated spectral analysis as a method of automatic classification of EEG data (Bronzino, 1984; Gersch & Yonemoto, 1977a; Gersch & Yonemoto, 1977b; Jansen, Bourne, & Ward, 1971; Ono & Kaminogo, 1981). To perform automatic classification, an algorithm operates on the spectral estimate data and classifies the behavior of the EEG subject. Monitoring a patient under anesthesia is an example of where automatic classification has been used.

The advantages and disadvantages of both the Fourier and modern methods of spectral analysis as applied to EEG signals will now be discussed. Then the Fourier method of EEG analysis will be compared to the modern methods. Finally, the differences between the modern methods as applied to EEG signals will be discussed.

(1) Fourier Techniques

The Fourier method as applied to EEG spectral analysis has been used by many researchers (Bronzino, 1984; Dolce & Kunkel, 1975; Dumermuth & Fluhler, 1967; Gersch, 1970; Gevins & Yeager, 1972; Grass & Gibbs, 1983; Matousek, 1967; Walter, 1963;).

As mentioned above, the Fourier method has the advantage of computational efficiency. However, the computational advantage decreases with decreasing data length so computational efficiency becomes less of an advantage for short data record EEG signals. Also, many applications do not require EEG analysis to be done in real time. In these applications more importance is placed on an accurate result rather then computational speed. The Fourier method does have an advantage of always producing a stable model and this characteristic applies equally well to EEG analysis.

The Fourier method has a definite disadvantage from the standpoint of frequency resolution if short EEG data records are to be analyzed. Accurate estimation of the frequency of a peak will not be possible. Also, sidelobes due to the windowing of the data will be a problem. For example, if there is high level activity at 7 Hz, the sidelobes from this peak could completely cover low level activity in the alpha (8 - 12 Hz) region.

(2) Modern Methods

More recently, researchers have investigated the use of modern methods of spectral estimation to analyze EEG signals (Bohlin, 1973; Fenwick, Michie, Dollimore & Fenton, 1971; Gersch, 1970; Gersch & Yonemoto, 1977a; Gersch & Yonemoto, 1977b; Gevins, Yeager, Diamond, Spire Zeitlin & Gevins, 1975; Heinze, Kunkel & Massing, 1981; Jansen, Bourne, & Ward, 1971; Ono & Kaminogo, 1981; Pfurtscheller & Haring, 1972). If short EEG data records

are to be analyzed, the modern methods will have good frequency resolution performance. This is very important in EEG analysis because the location of peaks and the small movement of peaks can provide insight into the functioning of the brain. The advantage of no implied windowing of the data (except for the YW method) is also important in EEG analysis. Low level brain activity which is close in frequency to high level activity will not be covered by sidelobes.

A very interesting interpretation of EEG spectral analysis by modern methods has been proposed by Fenwick, Michie, Dollimore and Fenton (1971). They have suggested that the EEG signal is the sum of the output of "generators", or large pools of neurons. The AR coefficients define a filter which processes a random input to produce a signal which models the output of these generators. A change in AR coefficients suggests a change in the activity of the generators. Furthermore, they have suggested that the AR model is the same filter for both evoked and spontaneous activity. Therefore, the evoked EEG can be predicted from the spontaneous EEG by finding the impulse response of the filter. The impulse response will show how generators respond to evoked activity. The researchers who proposed this theory have shown experimental results which support it.

As mentioned above, model order selection is a problem of the modern methods. However, in practice, determining the model order has not been a problem. Many researchers have reported that an AR model order of about ten is sufficient for a wide range of EEG signals (Akaike, 1981; Bourne, & Ward, 1971; Gersch, 1970; Gersch & Yonemoto, 1977a; Jansen, Bohlin, 1973; Ono & Kaminogo, 1981). Also, Gersch and Yonemoto (1977a) have reported that both AR and ARMA models of EEG signals are insensitive to slight overparameterization. This means that spectral estimates using models of correct order will be very similar to models which are slightly higher in order and spectral line splitting will be unlikely. Another disadvantage of the modern methods is that the LS method can produce unstable models. However, this is not a problem when spectral analysis is being performed and for most data, stable models are produced (Kay & Marple, 1981; Marple, 1980; Nutall, 1976). No mention of the problem of unstable generalized least squares models has been found in the EEG literature.

Differences exist between the modern methods of spectral estimation when applied to EEG signals. The AR and ARMA methods of spectral analysis as applied to EEG signals have been compared (Bohlin, 1973; Gersch & Yonemoto, 1977; Pfurtscheller & Haring, 1972). The spectral estimates are usually extremely similar but the AR method requires less computation. The ARMA model requires specification of both the moving average order, q, and the autoregressive order, p, but the AR model only requires the

specification of p. For these reasons, the AR models are usually chosen for EEG analysis. The Kalman filtering approach has the advantage that it will adapt to changes in the signal properties if the signal is non-stationary. However, there is a question as to whether the adaptation is fast enough for EEG signals, especially short length EEG signals (Jansen, Bourne, & Ward, 1971). The Kalman filtering method could prove to be a very useful method of analysis (especially for non-stationary EEG signals) but more investigation of this method needs to be done. As mentioned previously, the YW method has the advantage of better frequency resolution than the Fourier method, but like the Fourier method it has the disadvantage of implied windowing. These characteristics also apply when the YW method is used for EEG analysis. The LS or Burg method can be used to get the advantages of frequency resolution and no implied windowing.

(3) A Comparison of the Two Approaches

Many comparisons have been made between the Fourier approach and the modern methods of spectral estimation as applied to EEG analysis (Akaike, 1981; Fenwick, Michie, Dollimore & Fenton, 1971; Gersch, 1970; Gersch & Yonemoto, 1977a; Gersch & Yonemoto, 1977b; Heinze, Kunkel & Massing, 1981; Jansen, Bourne, & Ward, 1971; Pfurtscheller & Haring, 1972). In general, the spectral estimates of EEG signals produced by the Fourier and modern methods are very similar, but some differences do exist. The modern methods (the LS method in particular) have the advantage that the EEG spectrum is smoother and easier to interpret (Gersch, 1970; Gersch & Yonemoto, 1977a; Jansen, Bourne, & Ward, 1971; Kunkel, 1977). Peaks are more pronounced and therefore less subjective judgement is required to interpret and classify the EEG data. Gersch (1970) has shown evidence that the smoothing of the AR methods is not arbitrary. This was shown by processing data which had a known spectrum. The LS estimate was not only smoother than the Fourier estimate, but it also gave an estimate closer to the theoretical value.

As mentioned above, the Fourier method has the advantage that less computation is needed, but this is important only for long EEG data sequences or if the EEG data needs to be quickly analyzed. The modern methods have the advantage of data reduction. Usually only about ten coefficients are needed to describe the signal. Data reduction is an advantage because less storage capacity is needed and also less data needs to be manipulated in automatic classification algorithms. The modern methods also have the advantage over the Fourier method that the concept of generators can be used. This theory may allow evoked responses to be predicted from spontaneous responses, although this topic has not been thoroughly investigated.

C Experimental Results

Based on the arguments in Section B, it was determined that the best modern method for application to short record length EEG signals was the LS algorithm. This algorithm was coded in FORTRAN, and its performance tested under a variety of conditions.

Experiments were performed to compare the FFT and LS methods of spectral analysis. The methods were each used to analyze three different classes of signals -- deterministic and randomly corrupted signals of known spectra, and actual EEG data of unknown spectra. Deterministic signals, or those with no random components were analyzed first. The signals of known spectra were generated in software and analyzed with computer program implementations of the FFT (IEEE, 1979) and LS (Marple, 1980) algorithms. This portion of the experiment allowed comparison of the estimated spectra with theoretical results. The EEG signals have unknown spectra so it is difficult to determine the accuracy of the estimates. However, the analysis of deterministic signals provided insight into the strengths and weaknesses of each method of spectral analysis. This insight provided valuable clues to help determine the accuracy of the EEG spectral estimates.

Before comparing the different spectral estimates it is important to remember a basic difference between the FFT and LS methods. The FFT generates values for the spectral estimate only at specific frequencies whereas the LS estimate is continuous in nature. The spacing between samples for the FFT estimate can be calculated using:

$$\Delta f = \frac{1}{N \Delta t} \tag{12}$$

where: N = number of samples
Δt = time between samples

The apparent continuous nature of the FFT estimates in the figures presented is a consequence of the graphing routine which connects adjacent samples using a straight line. Even though the LS estimate is a continuous estimate samples must be calculated to facilitate graphing by a digital computer. The spacing between samples for the LS was chosen to be 0.005 Hz.

1 Deterministic Signals

Two specific deterministic signals were chosen for analysis. The first signal consisted of two sinusoids described by:

$$s_1(n) = \sin(2\pi n \Delta t 3.2) + \sin(2\pi n \Delta t 13.5) \qquad (13)$$

where: $\Delta t = 5/512$ seconds
$n = 0,1,2,\ldots N-1$

The time between samples for the deterministic signals was chosen to be equal to the time between samples for the actual EEG data so that easy comparisons could be made. Analysis was performed for two different values of N. The value of N=64 was chosen to correspond to the length of the EEG data. A value of N=512 was also used to illustrate differences between long and short data records.

In terms of spectral broadening, the frequencies of 3.2 and 13.5 Hz were chosen to represent best-case and worst-case signals for the FFT. The case where N=512 meant $\Delta f = 0.2$ Hz. Therefore 3.2 Hz was exactly at a frequency sample and represented a best-case situation. The frequency component at 13.5 Hz lies halfway between frequency samples and represented a worst-case signal in terms of spectral broadening.

Figure A-1 shows the spectral estimates of equation (13) for the case where N=512. The estimates have been normalized so that the maximum value for each estimate is 0 dB. Ideally, the estimates would consist of impulses at 3.2 and 13.5 Hz corresponding to the Fourier transform of an infinite length signal. The actual signals are, of course, of finite length and this causes spreading of the impulses.

Equal amplitudes were chosen for the two input frequency components and therefore the magnitude of the spectral estimates should ideally be equal. However, the peaks of the FFT estimates differ by 3.9 dB with the 3.2 Hz peak being the larger. This represents a worst case situation in terms of amplitude difference performance for the FFT method. The peaks of the LS estimate differ by 10.8 dB with the 13.5 Hz peak being the larger. Therefore, for this case and in most other cases which were observed, the FFT estimate provided more accurate relative amplitude information for sharp peaks in the spectrum.

Careful interpretation of the results is required when comparing the width of the peaks. The FFT estimate of the signal at 13.5 Hz has a large width because this frequency lies midway between FFT frequency samples. Energy from this signal is spread into other frequency samples. The signal at 3.2 Hz lies exactly at a frequency sample of the FFT estimate and energy from this signal will not spread into other frequency samples. Comparison shows the LS estimate has a much smaller width than the FFT estimate for the 13.5 Hz signal. For the 3.2 Hz signal the FFT estimate has superior performance because it has energy at only one sample point and therefore has no width. However, the energy

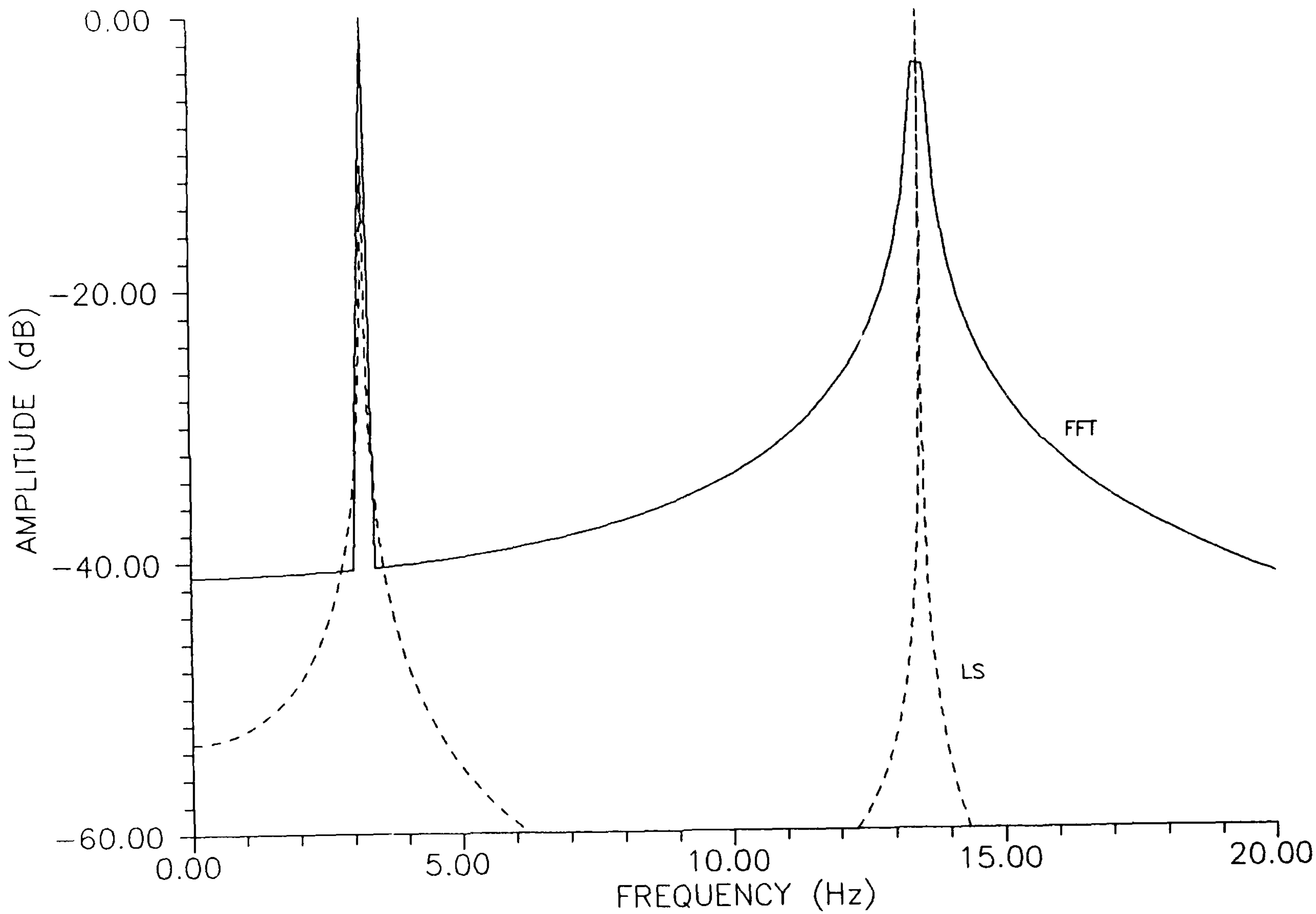

Figure A-1. LS and FFT Spectral Estimates for the Two Sinusoids of Equation 13 with N=512.

of the FFT estimate of the signal at 13.5 Hz does not fall off rapidly and for frequencies near 3.2 Hz it is even larger than the energy of the LS estimate.

Figure A-2 shows the effect of decreasing the number of samples to N=64. For this shorter sequence the samples of the FFT estimate are now spaced in frequency by 1.6 Hz so that the 3.2 Hz component still lies at a frequency sample and the 13.5 Hz component lies close to halfway between samples. As shown in Figure A-2, the peaks of the FFT estimate have broadened considerably and have caused extreme distortion in the shape of the spectrum. The broadening of the peaks for the FFT estimate is proportional to 1/T where T equals the length of the time domain signal. Therefore, the FFT method produces a poorer estimate for shorter data records because broader peaks are produced. Increasing the sampling rate will increase the number of samples but will not decrease the broadening for a fixed value of T. To improve the FFT estimate T must be increased. However, this may not be possible in many applications such as for the case of analyzing EEG events lasting a fixed amount of time.

The amplitude of the peaks of the FFT estimate for N=64 differ in magnitude by 2.9 dB while those of the LS estimate differ by 11.4 dB indicating that despite the broadening the FFT still has superior amplitude estimation performance.

To further investigate these topics, a second deterministic signal was analyzed. The signal is described by:

$$s_2(n) = \exp\left\{ - \mid n - \frac{N}{2} + 1 \mid \Delta t 5 \right\} \tag{14}$$

where: $n = 0, 1, 2, \ldots N-1$

$\Delta t = 5/512$ seconds

which for the case of a continuous, infinite length signal has the Fourier transform (Bracewell, 1978):

$$S_2(f) = \frac{2}{1 + \left(2\pi \frac{f}{5}\right)^2} \tag{15}$$

The transform of this signal is a smooth and continuous function of frequency unlike the impulses for the first signal analyzed. A signal with a smooth spectrum was chosen so that the performance of the estimation methods for this type of signal could be determined. Figure A-3 shows the estimates for N=512 with $S_2(f)$ plotted for comparison. Both the FFT and LS methods generate excellent spectral estimates. Figure A-4 shows the effects of decreasing N to 64. The LS estimate is almost unchanged. The FFT estimate has become rough although the

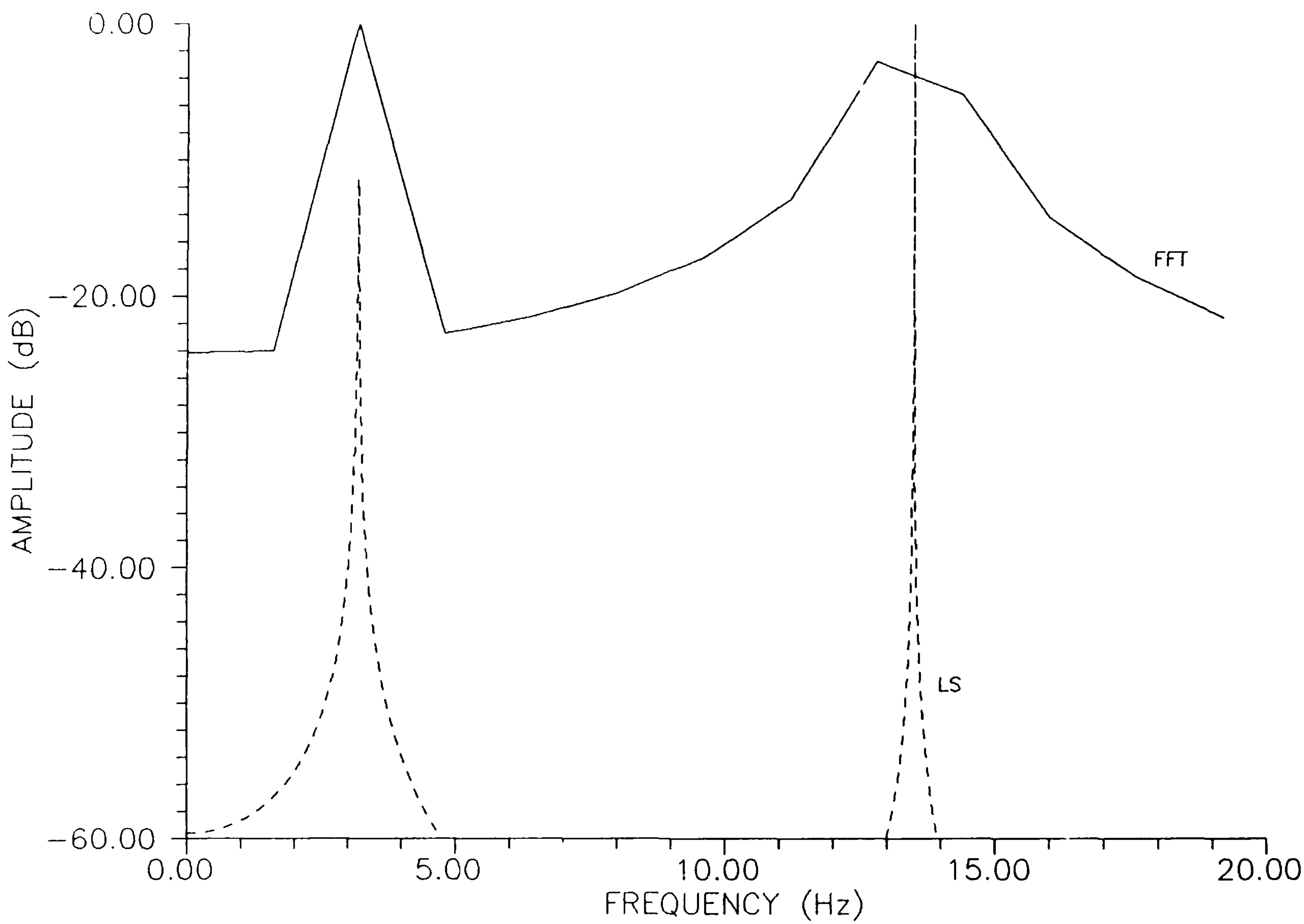

Figure A-2. LS and FFT Spectral Estimates for the Two Sinusoids of Equation 13 with N=64.

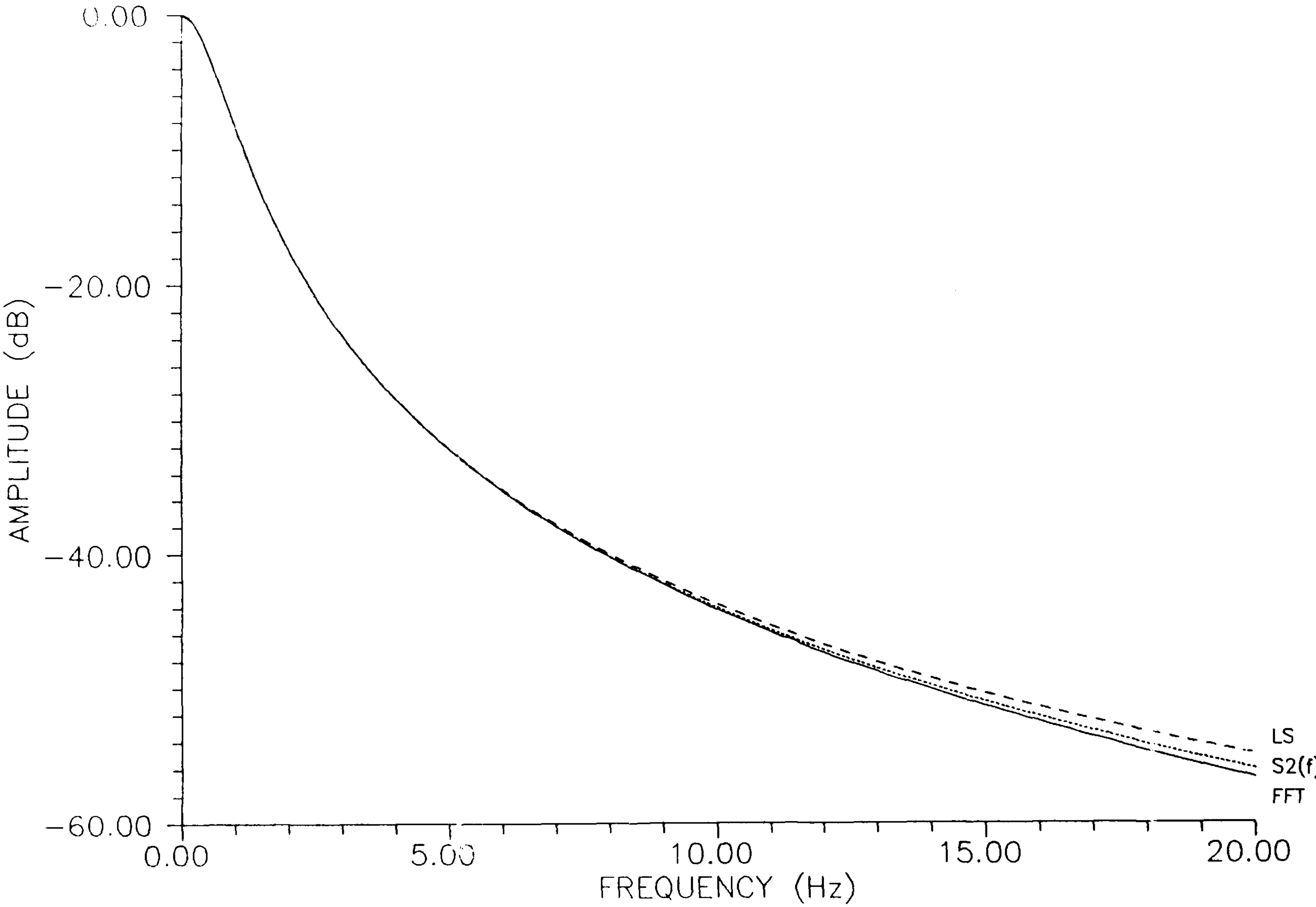

Figure A-3. LS and FFT Spectral Estimates for the Exponential Signal of Equation 14 with N=512.

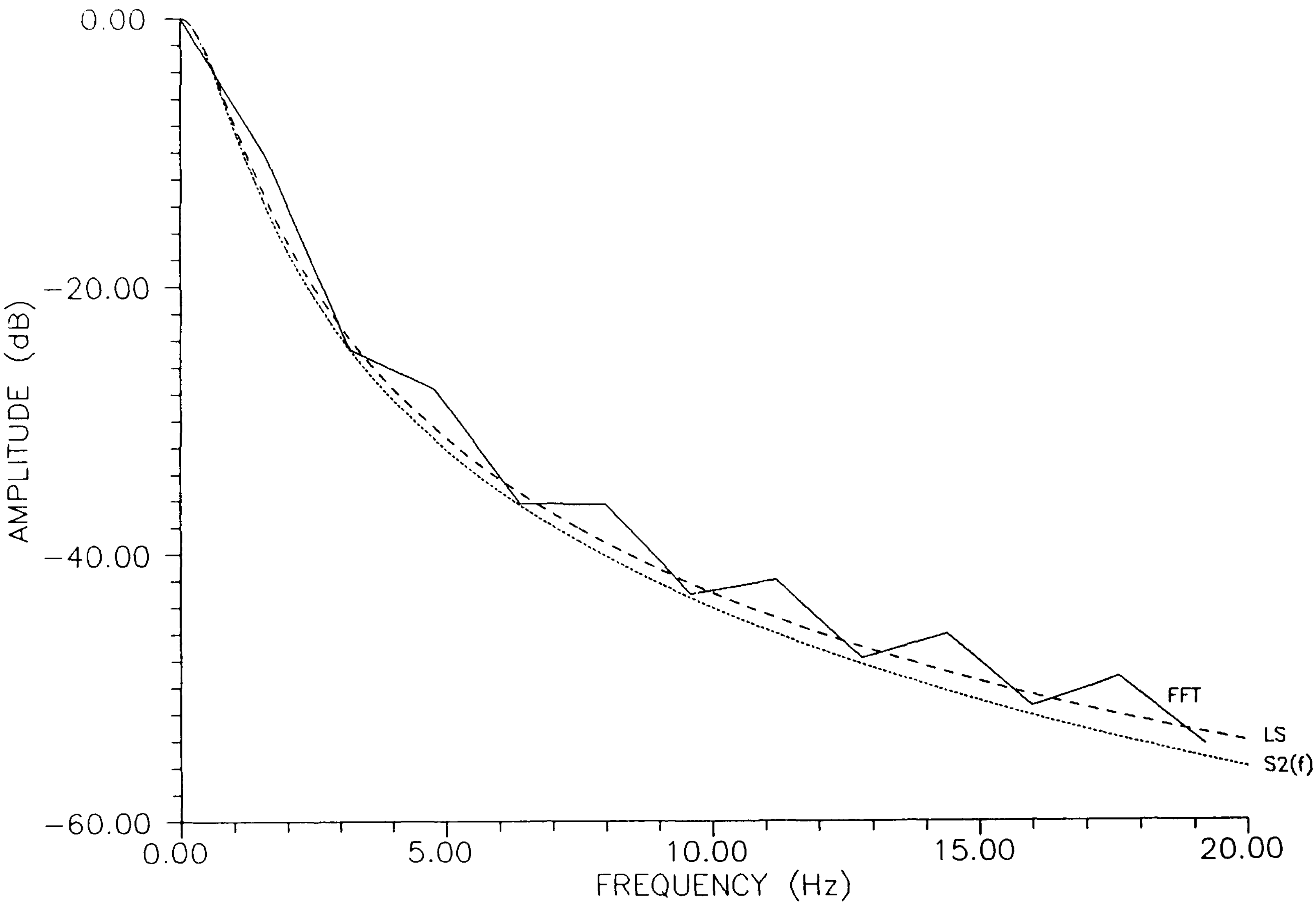

Figure A-4. LS and FFT Spectral Estimates for the Exponential Signal of Equation 14 with N=64.

average value is very close to the LS estimate. This characteristic of the LS method generating a smoother estimate was observed quite frequently for both simulated signals and actual EEG signals.

From the above examples it appears that the FFT gives a good estimate for long sequences and has the advantage of computational efficiency. For short sequences the FFT has superior relative amplitude estimation performance over the LS method although it has inferior frequency resolution and exhibits severe broadening of sharp peaks. These distortions to the FFT estimate are rarely acceptable and for short data sequences it appears that the FFT should only be used in conjunction with the LS method.

Two key observations can be made concerning the LS estimates. First, for both types of spectra analyzed, the estimates are nearly identical for the longer and shorter data records. Second, the estimates are very close to the spectra which would be obtained for a signal of infinite length. This shows that the LS estimate has little degradation for shorter length sequences. However, the LS method does not have the computational efficiency of the FFT and exhibits poor relative amplitude performance for spectra containing sharp peaks.

The above results suggest that both methods of spectral estimation could be used to estimate an unknown spectrum. The LS estimate could be used to find the general shape of the spectrum and the location of sharp peaks. The FFT estimate could be used to confirm the shape of smooth spectra and estimate the relative amplitude of sharp peaks.

2 Random Signals of Known Spectra

White Gaussian noise was added to the deterministic signals described above and spectral estimates were computed. The purpose of this section was to determine the effect of noise on the spectral estimates. The case of N=64 was investigated for various ratios of signal power to the two-sided noise spectral density, S/N_0 . The noise spectral density is calculated by:

$$N_0 = \sigma^2 \frac{\Delta t}{2} \tag{16}$$

where: σ^2 = variance of the noise

Although the noise was random, for ease of comparison the same noise was added for all cases analyzed. Spectral estimates for only the noise signal, whose actual spectra is specified by a flat horizontal line, are shown in Figure A-5 The LS estimate is of model order 16 and varies over a range of about 5 dB while the FFT estimate varies over about 13 dB. The estimates show very

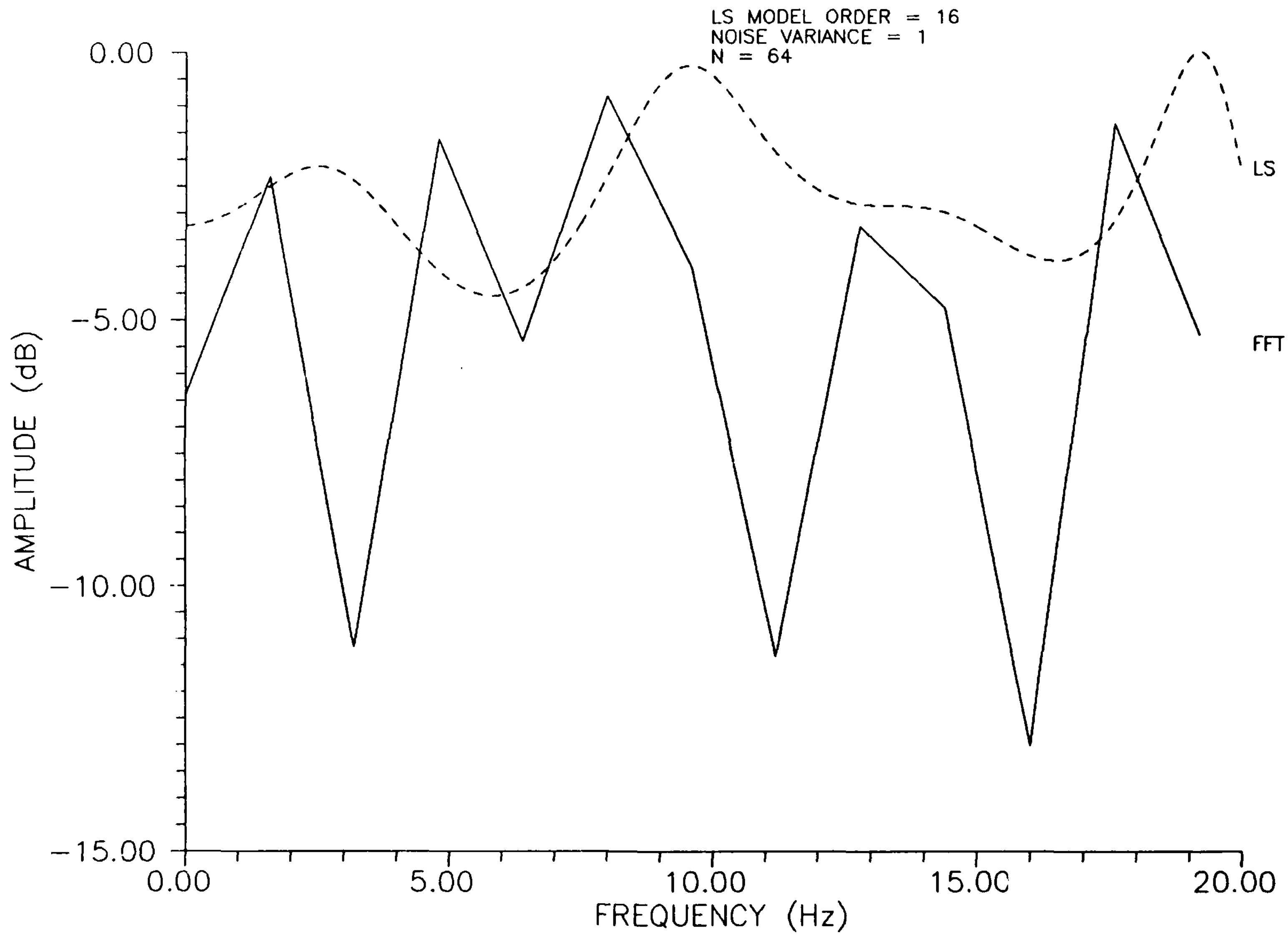

Figure A-5. LS and FFT Spectral Estimates of Noise Added to Deterministic Signals.

little similarity except that each estimate has a slight peak near 9 and 18 Hz. The LS estimate is much smoother than the FFT estimate, a characteristic seen for the deterministic signals. It should be noted that the amplitude level shown for the LS estimate in Figure A-5 is arbitrary. The S/N_0 ratio is the important parameter in the following plots.

Figure A-6 shows the estimates for the two sinusoids in noise with S/N_0 set equal to 2,000. The signal power for the sinusoids was chosen to be equal to the power of one sinusoid which can be calculated by:

$$S = \frac{A^2}{2} \qquad (17)$$

where: A = zero-to-peak amplitude of sinusoidal component

Comparison of the FFT estimate with Figure A-2 shows that it is similar to the estimate with no noise present. The DC value for the added noise case is lower but the region between 5 and 12 Hz shows more energy present. The LS estimate shows a large increase in the regions adjacent to and between the peaks. This will limit the dynamic range of the LS estimate but it is still much better than the FFT. The levels of the peaks for the LS estimate now differ by only about 2 dB which is comparable in performance to the FFT estimate.

Next the S/N_0 ratio was decreased to 100. Spectral estimates are shown in Figure A-7 It is now hard to distinguish two well defined peaks in the FFT estimate. The roughness of the estimate and the high levels adjacent to the peaks make it difficult to determine that the time domain signal consists of two sinusoids in white noise. The LS estimate is fairly flat except for two broadened peaks and gives a better indication of the time domain signal.

Finally, the noise was added to the exponential signal, $s_2(n)$. For this case the signal power can be calculated by:

$$S = 0.306 A^2 \qquad (18)$$

where: A = maximum value of $s_2(n)$

Figure A-8 shows the spectral estimates for $S/N_0 = 50{,}000$ with an LS model order of 16. Also plotted in Figure A-8 is $S_2(f) + N_0$, the Fourier transform of a continuous, infinite length version of $s_2(n)$ with added white noise of two-sided spectral density N_0. Because the spectrum of this signal spanned a wide range of amplitudes, it was necessary to use a lower noise level here in order to properly examine the performance of the estimator over the full signal bandwidth. For this case the FFT provides a

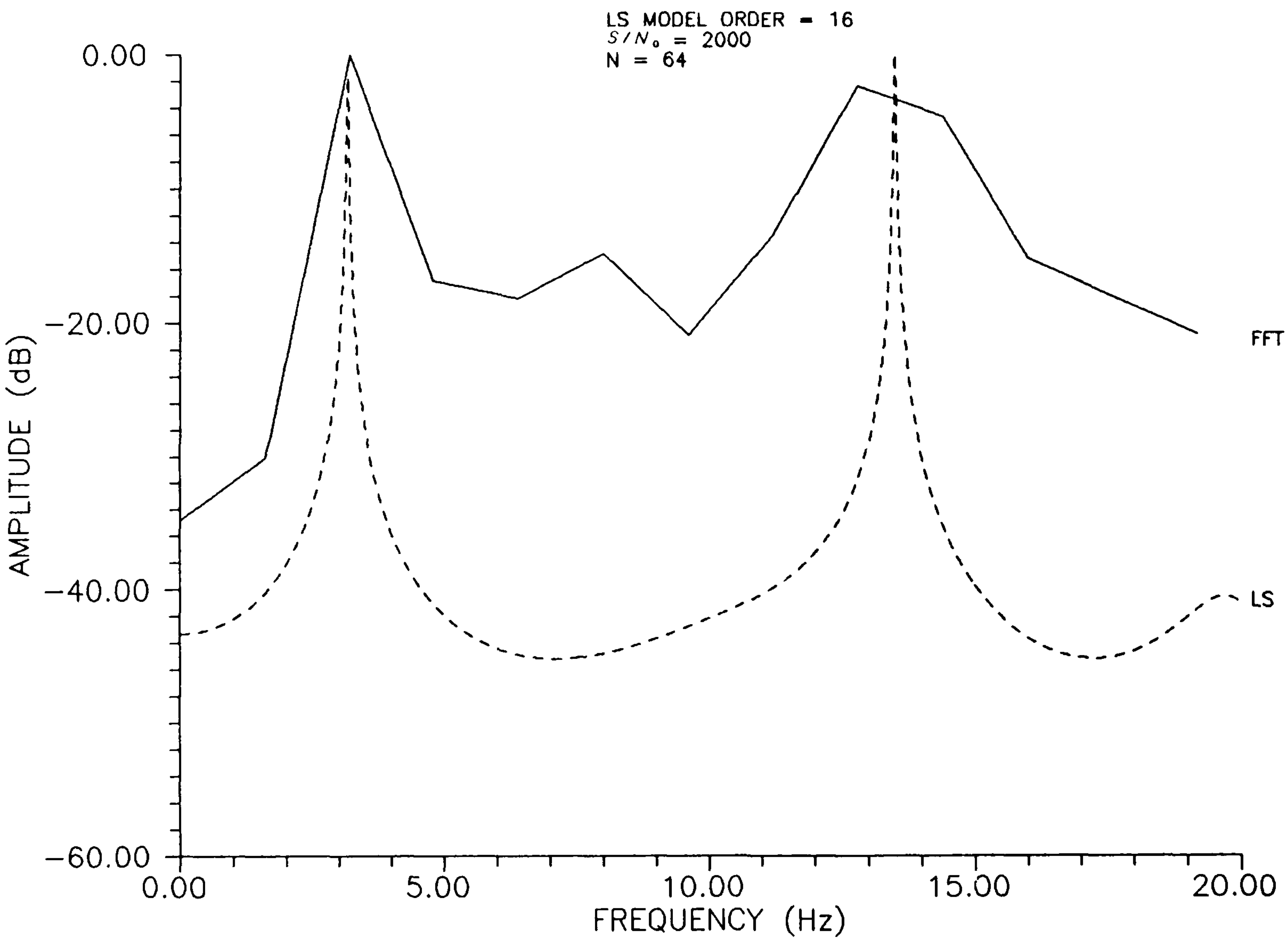

Figure A-6. LS and FFT Spectral Estimates for the Two Sinusoids of Equation 13 with Added Noise.

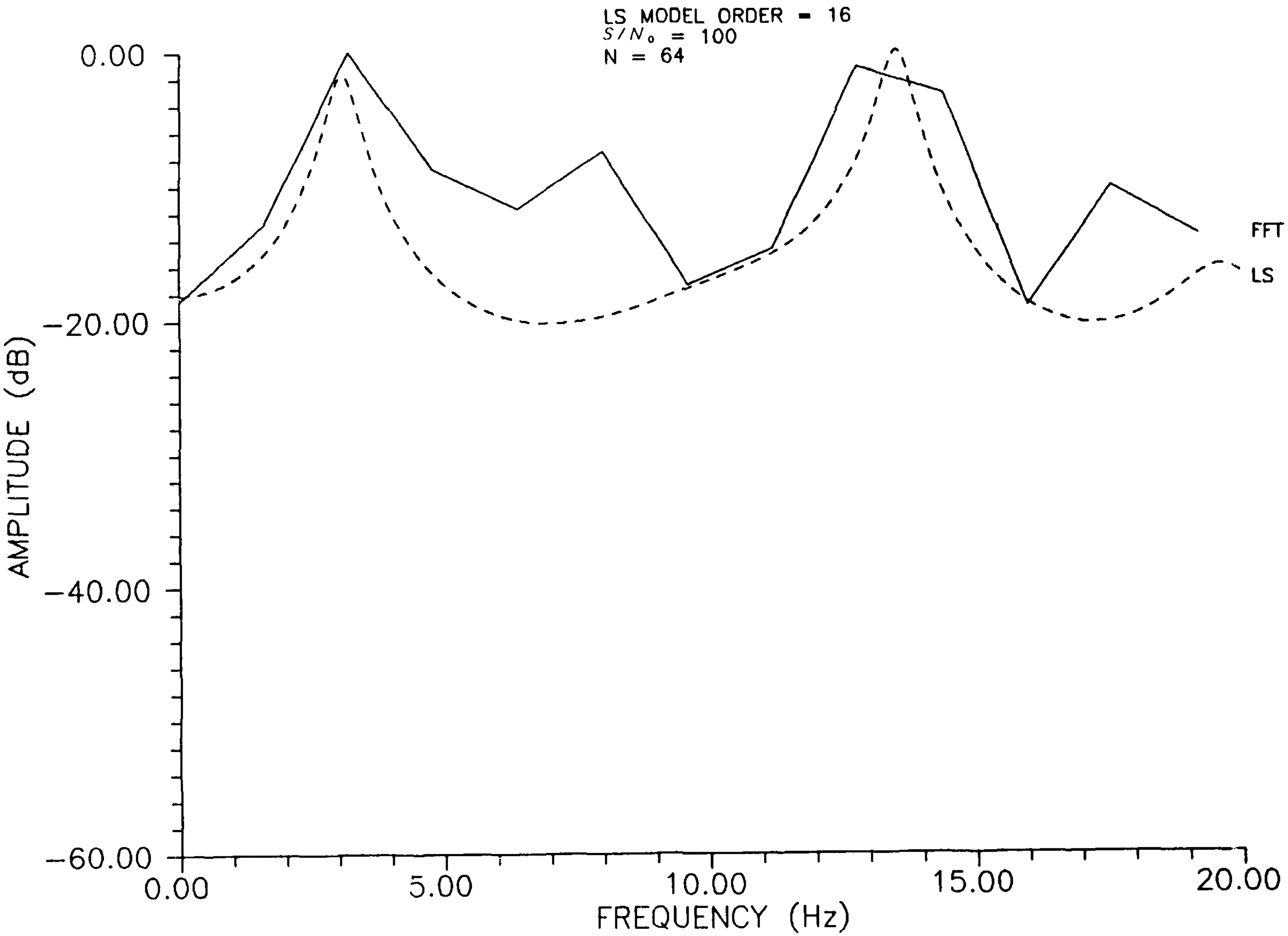

Figure A-7. LS and FFT Spectral Estimates for the Two Sinusoids of Equation 13 with Added Noise.

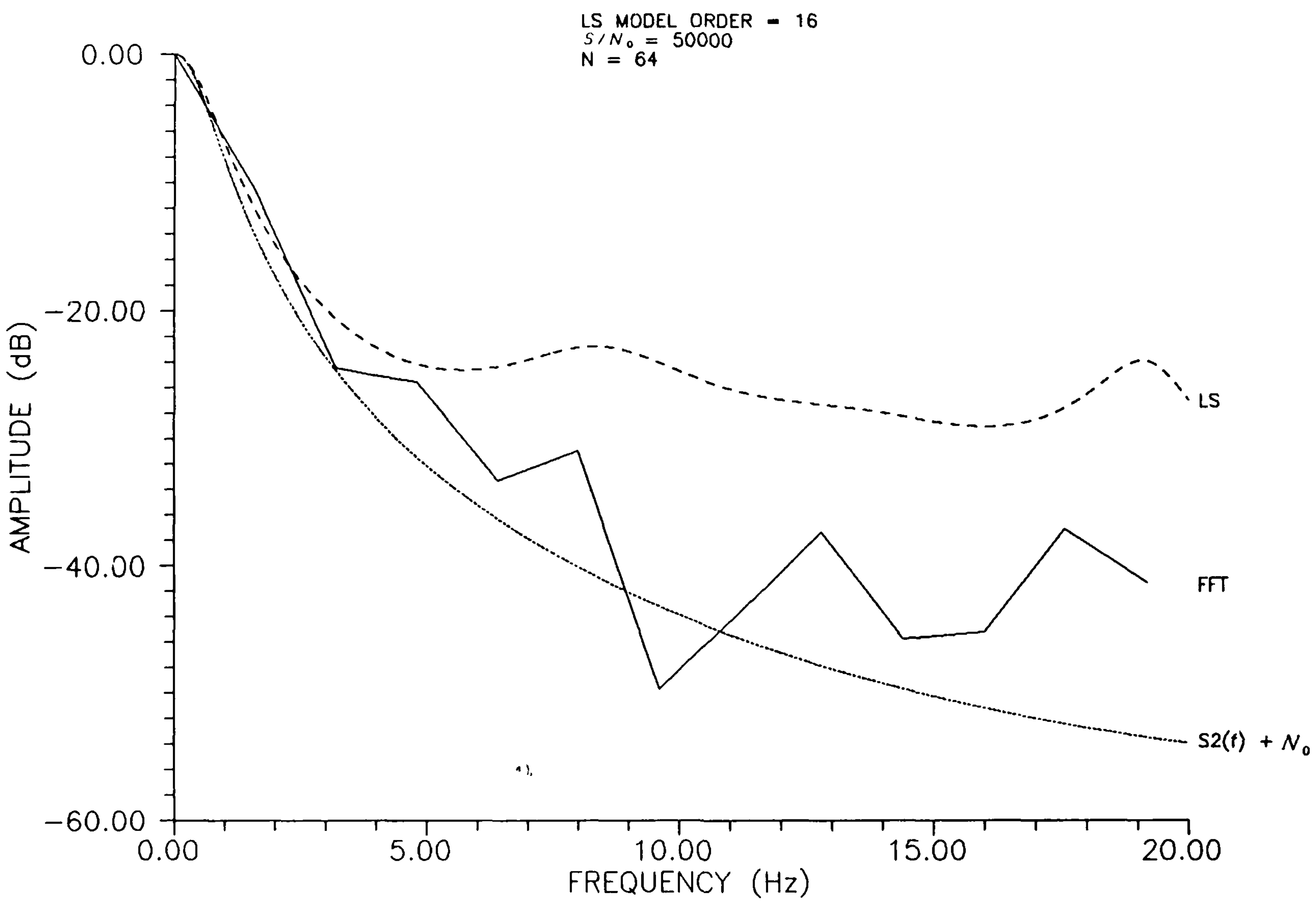

Figure A-8. LS and FFT Spectral Estimates for the Exponential Signal of Equation 14 with Added Noise.

better estimate than the LS algorithm. Even though the FFT estimate shows too much energy in the higher frequencies, it provides a spectrum closer to theoretical than the LS algorithm.

A lower LS model order was used on the same data and the results are shown in Figure A-9 The LS estimate has improved and is now closer to theoretical than the FFT estimate. This indicates that although the LS method can still provide a better estimate than the FFT, the model order selection is more sensitive when noise is present.

The S/N_0 ratio was decreased to 10,000. Figure A-10 shows the spectral estimates with the LS model order set equal to 16. As seen previously for the LS model order of 16, the FFT estimate is better than the LS estimate. Comparison with Figure A-8 shows that both estimates have been degraded. The estimates provide agreement with the theoretical only for frequencies less than 5 Hz.

Again a lower LS model order was used. Results for a LS model order 6 are shown in Figure A-11. The low frequency part of the LS estimate is slightly degraded but for high frequencies the LS estimate is greatly improved and is better than the FFT estimate. For this S/N_0 ratio, LS model orders of 4 and 8 were also used. The estimates for these model orders were poor and inferior to the FFT estimate. This indicates that as S/N_0 is decreased, the LS model order selection becomes very critical.

From the above experiments it was seen that neither method of spectral estimation was clearly superior when noise was added to the signals. For high S/N_0 ratios the LS estimates were better than the FFT, but only if the LS model order was carefully chosen. This presents a problem when working with signals having unknown spectra because small changes of model order can result in large changes in the spectral estimates, making the proper model order difficult to determine. As the S/N_0 ratio was lowered, both methods of spectral estimation showed serious degradation and the LS model order selection became critical for the exponential signal.

Much lower values of S/N_0 could be used for the sinusoidal signals before the spectral estimates were degraded. However, it should be noted that to obtain a signal-noise-ratio (SNR), N_0 must be multiplied by the proper bandwidth, which is larger for the exponential signal. This means that the SNR for the two signals would be closer in value than the S/N_0 ratios.

3 Actual EEG Data

In this section, spectral estimates made from actual EEG data will be described. The data were taken from normal human subjects at rest. Before the data were input to the spectral

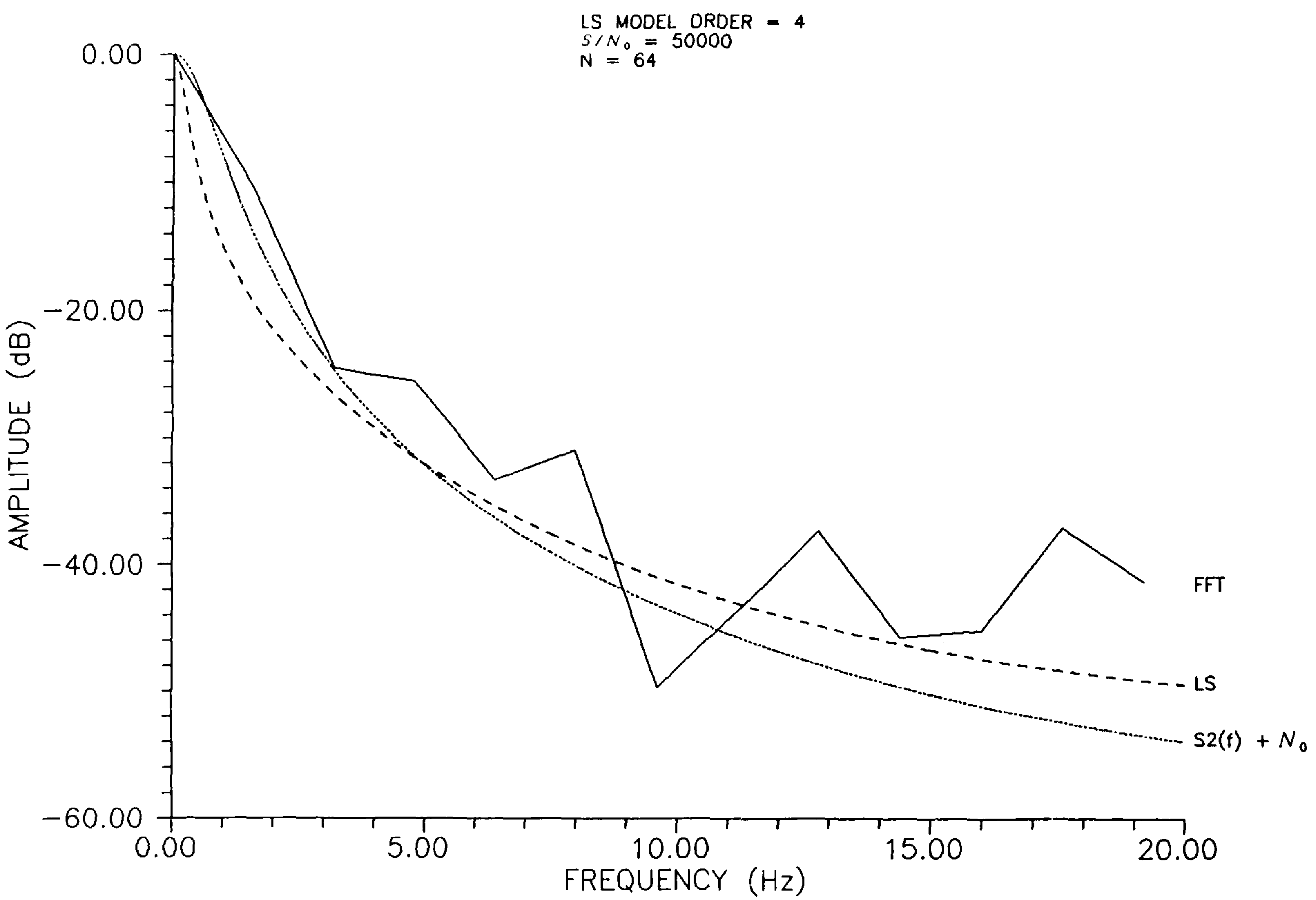

Figure A-9. LS and FFT Spectral Estimates for the Exponential Signal of Equation 14 with Added Noise.

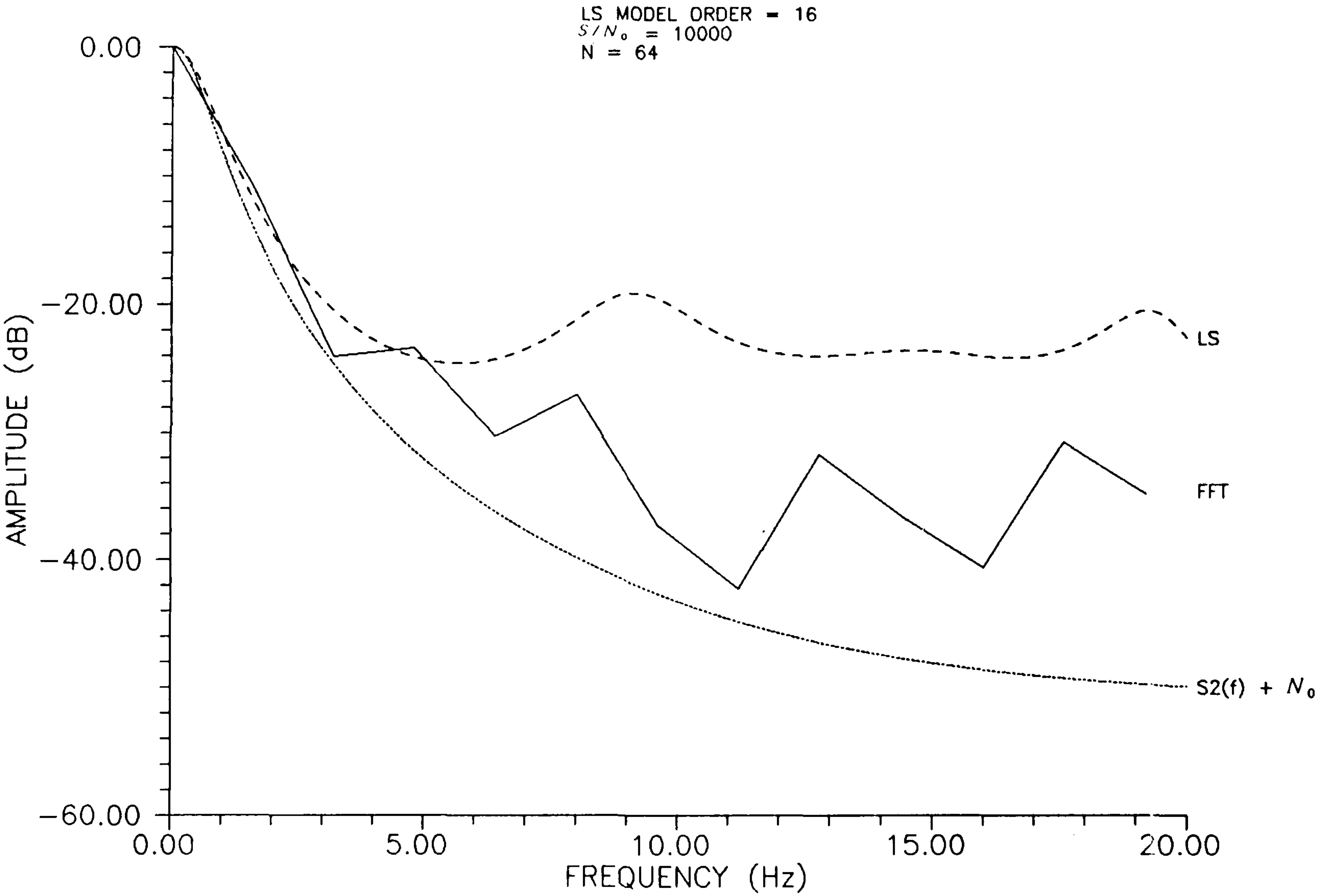

Figure A-10. LS and FFT Spectral Estimates for the Exponential Signal of Equation 14 with Added Noise.

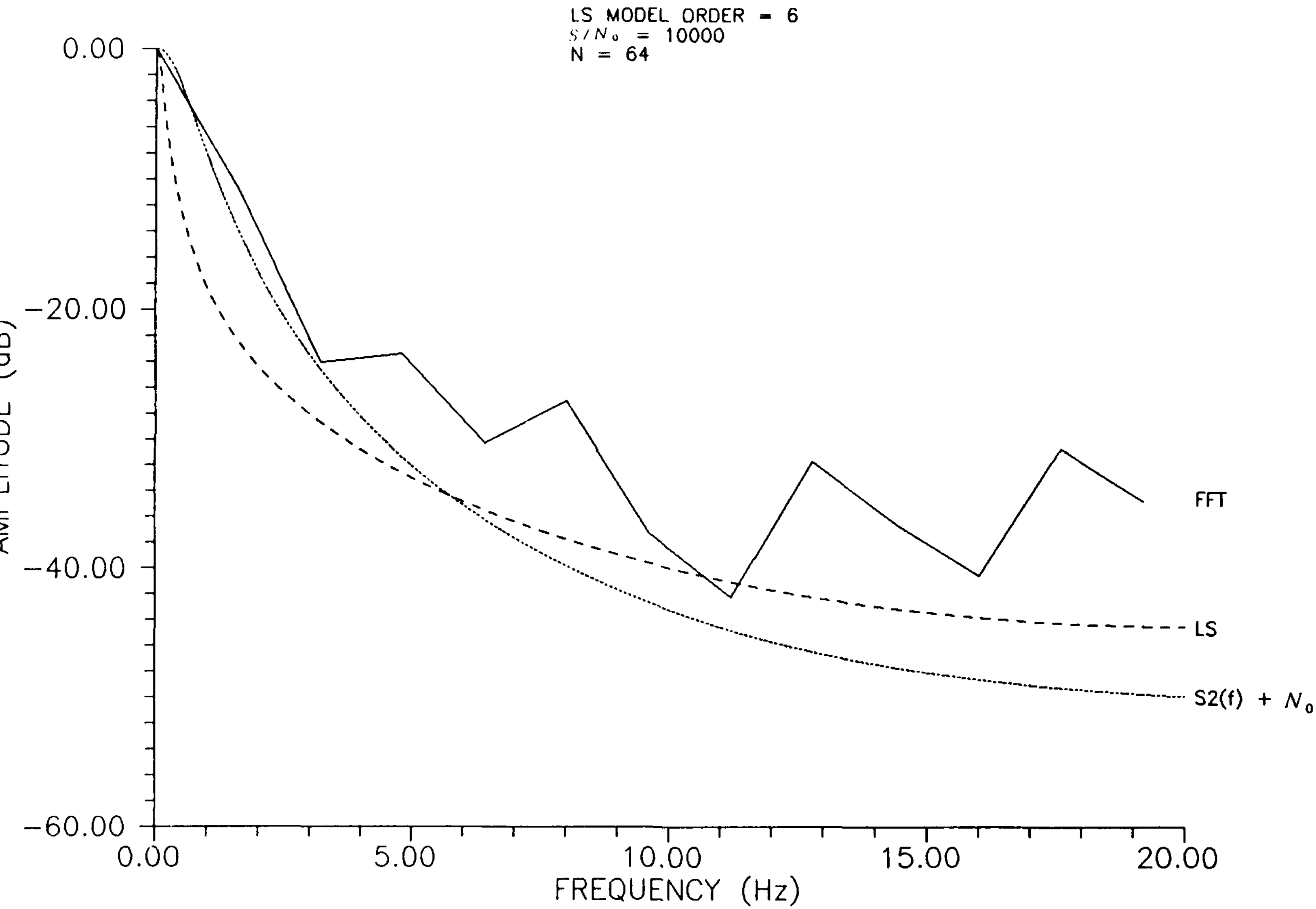

Figure A-11. LS and FFT Spectral Estimates for the Exponential Signal of Equation 14 with Added Noise.

estimation routines it was preprocessed as outlined in Figure A-12. The time spacing between samples was originally 1/512 seconds and the record length was 128 samples or 1/4 second. This meant according to the Nyquist sampling theorem that the highest frequency which could be analyzed without aliasing was 256 Hz. Even though only the 0-20 Hz region was of interest, the data were sampled at this rate so that input filters with nearly linear phase could be realized. However, linear phase was not of concern in this section of the experiment so it was desired to lower the sampling rate so that less data had to be processed. Lowering the sampling rate was accomplished by a process known as decimation -- forming a new sequence by selecting only every m^{th} sample from the original sequence. The decimation operation was preceded by a digital lowpass filter to prevent aliasing when the decimation operation was performed. For this specific application, the sampling rate was lowered by a factor of five so the decimation operation consisted of selecting every fifth sample. This changed the time between samples to 5/512 seconds. The length of the original data sequences was 128 samples. The lowpass filtering operation increased the number of samples to 170 because the filter was implemented with a 43 order finite impulse response (FIR) structure. The decimation by 5 then reduced the sequence length to 34. The FFT algorithm which was used required a data sequence length of a power of 2 so the sequence length was increased using zero-padding to 64.

As mentioned earlier, one problem with the LS routine is that the model order needs to be specified. If the model order is chosen too low then the spectral estimates tend to be too smooth. If too high of a model order is chosen then spurious and sharp peaks appear in the spectral estimate.

The LS routine which was used provided a type of automatic model order selection. First a spectral estimate was made based on a model order equal to one. Three parameters passed to the routine were then used to determine if a higher order model should be calculated. One parameter specified the maximum model order which could be calculated. The other two parameters were tolerances which were used by the routine to determine if a higher model order should be calculated. If it was determined based on the tolerances that a higher model order should be calculated and if the maximum model had not been reached then the next highest model order was calculated. This process was repeated until either the maximum model order was reached or the tolerances indicated that a satisfactory estimate had been generated.

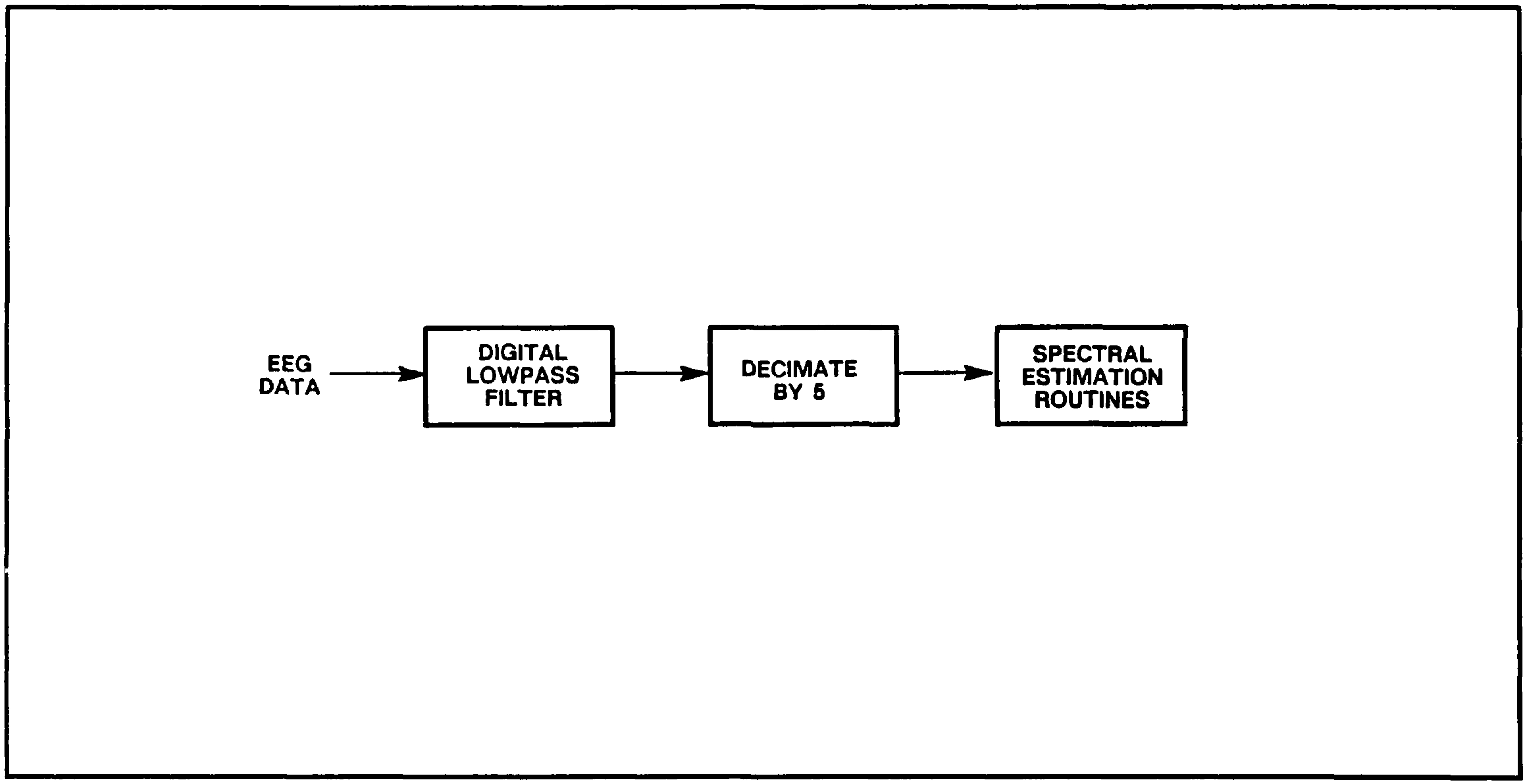

Figure A-12. Preprocessing of the Actual EEG Data.

Model order selection was not a problem for the deterministic signals. For a given signal, the same model order was chosen by the routine for an extremely wide range of tolerances. As seen in Figures A-1 through A-4, the LS estimates are very close to theoretical, indicating that the selected model order was neither too low nor too high.

Model order selection became more of a problem when EEG signals were analyzed. The tolerances could not be adjusted so that a proper model order was automatically selected by the LS routine for a large number of signals. However it was noticed that good results were obtained if the maximum model order was set to 16. With this maximum model order none of the signals analyzed produced estimates with a large number of sharp peaks. A large number of sharp peaks did not occur in any of the estimates until the model order was increased above 19 and sharp peaks did not occur in most estimates until the model order was increased above 23. This indicated that a model order of 16 was not too large. As the model order was reduced from 16 the estimates were very similar and did not show smoothing until the model order was reduced to about 12. This indicated that a model order of 16 was not too low.

It should be mentioned that we found the proper maximum model order to be dependent upon the length of the signal. Therefore, 16 may not be an appropriate choice of maximum model order for sequences of different length.

Examples of spectral estimates obtained from EEG data are shown in Figures A-13 throug A-16. When comparing plots it is important to keep in mind that the LS method does not produce an estimate for which the amplitude is proportional to the power in the signal. Instead, the LS estimate is an indication of the shape of the spectrum and the whole estimate may be shifted arbitrarily up or down in amplitude. A method was needed to determine the proper amount of shifting of the LS estimate for easy comparison with the FFT estimate. It was determined that neither setting the peak nor the average values of the corresponding FFT and LS estimates to be equal produced results which could be easily compared. Rather, a constant offset was added to the LS estimate and for most cases this produced results for which the FFT and LS estimates could be easily compared. The important point to note is that the shape of the LS estimate is of primary concern and the whole estimate may be shifted up or down.

Figure A-13 shows a case where the estimates are very similar. Each estimate shows four peaks in the spectrum at approximately the same frequencies. However, the FFT estimate produces peaks which appear to be broadened similarly to the peaks in Figure A-2. It is easy to see how the insight gained from the

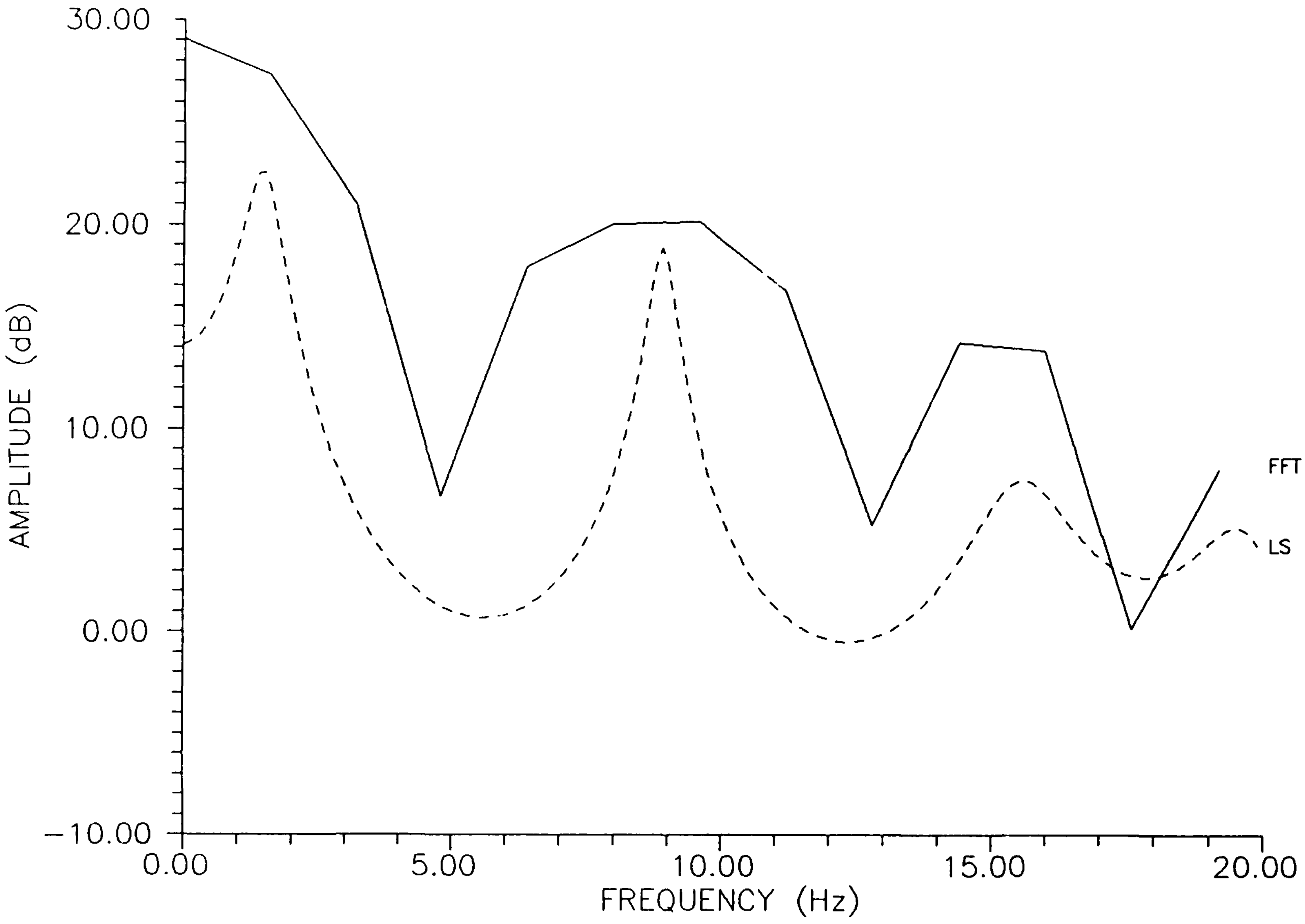

Figure A-13. LS and FFT Spectral Estimates of Actual EEG Data.

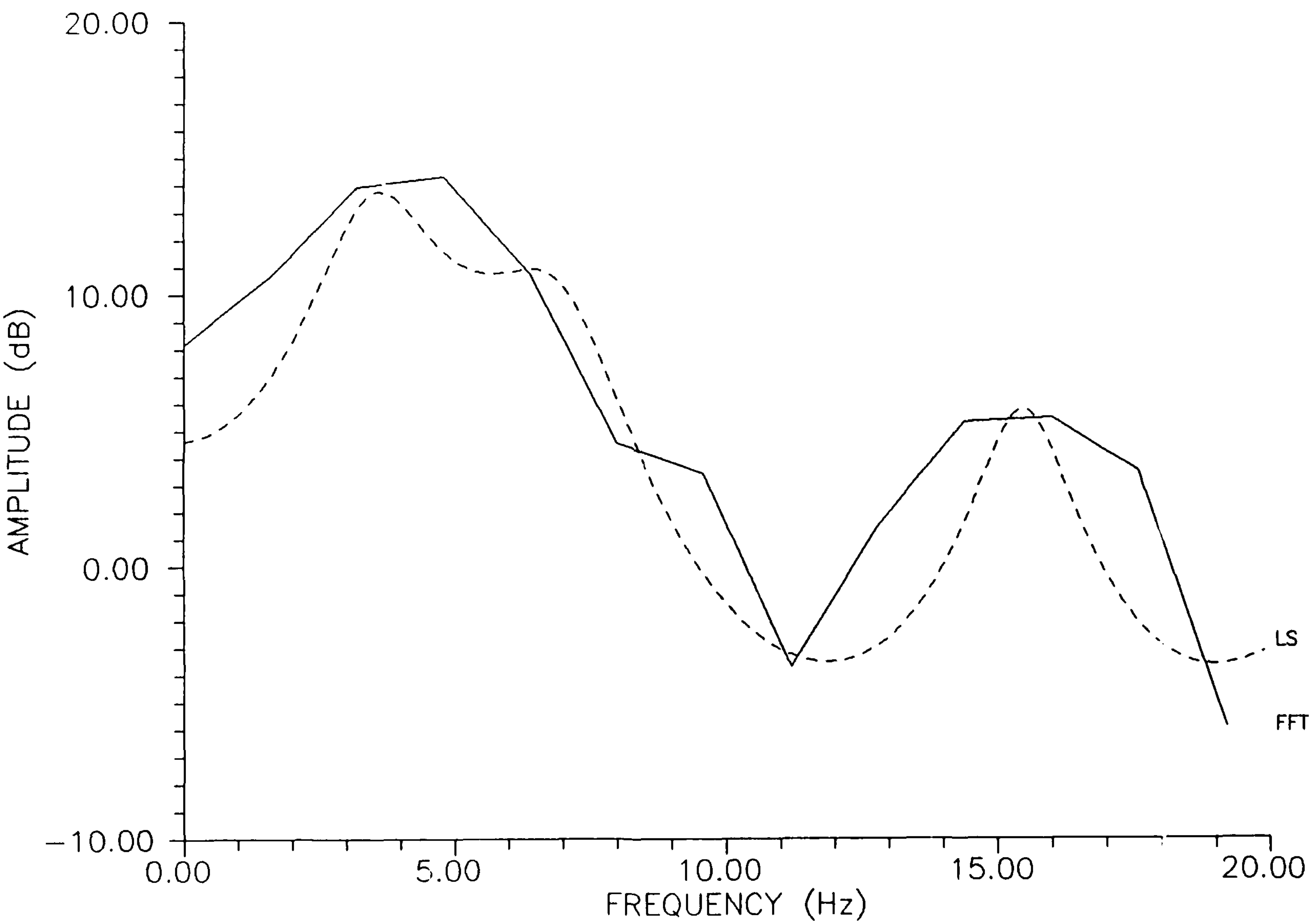

Figure A-14. LS and FFT Spectral Estimates of Actual EEG Data.

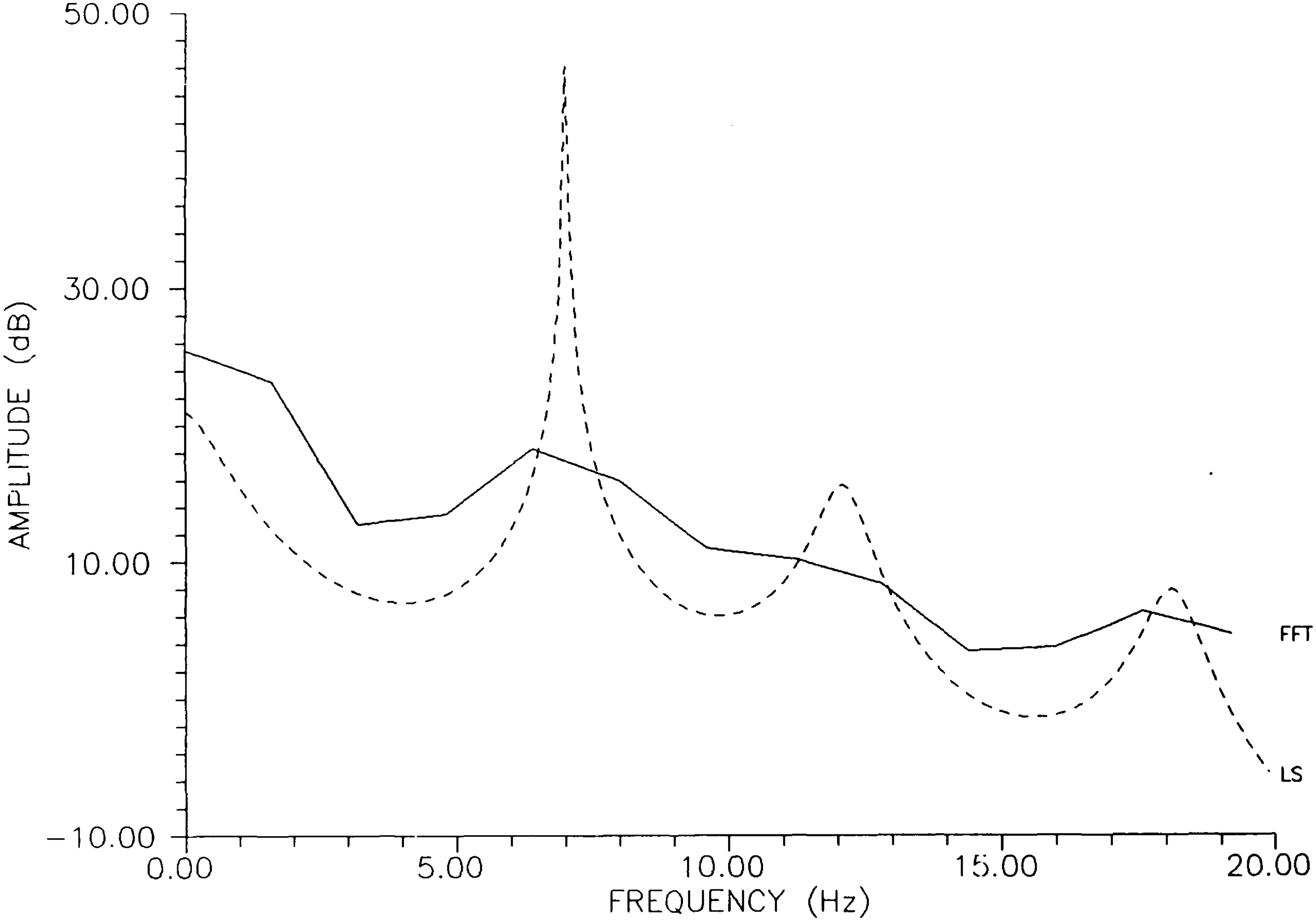

Figure A-15. LS and FFT Spectral Estimates of Actual EEG Data.

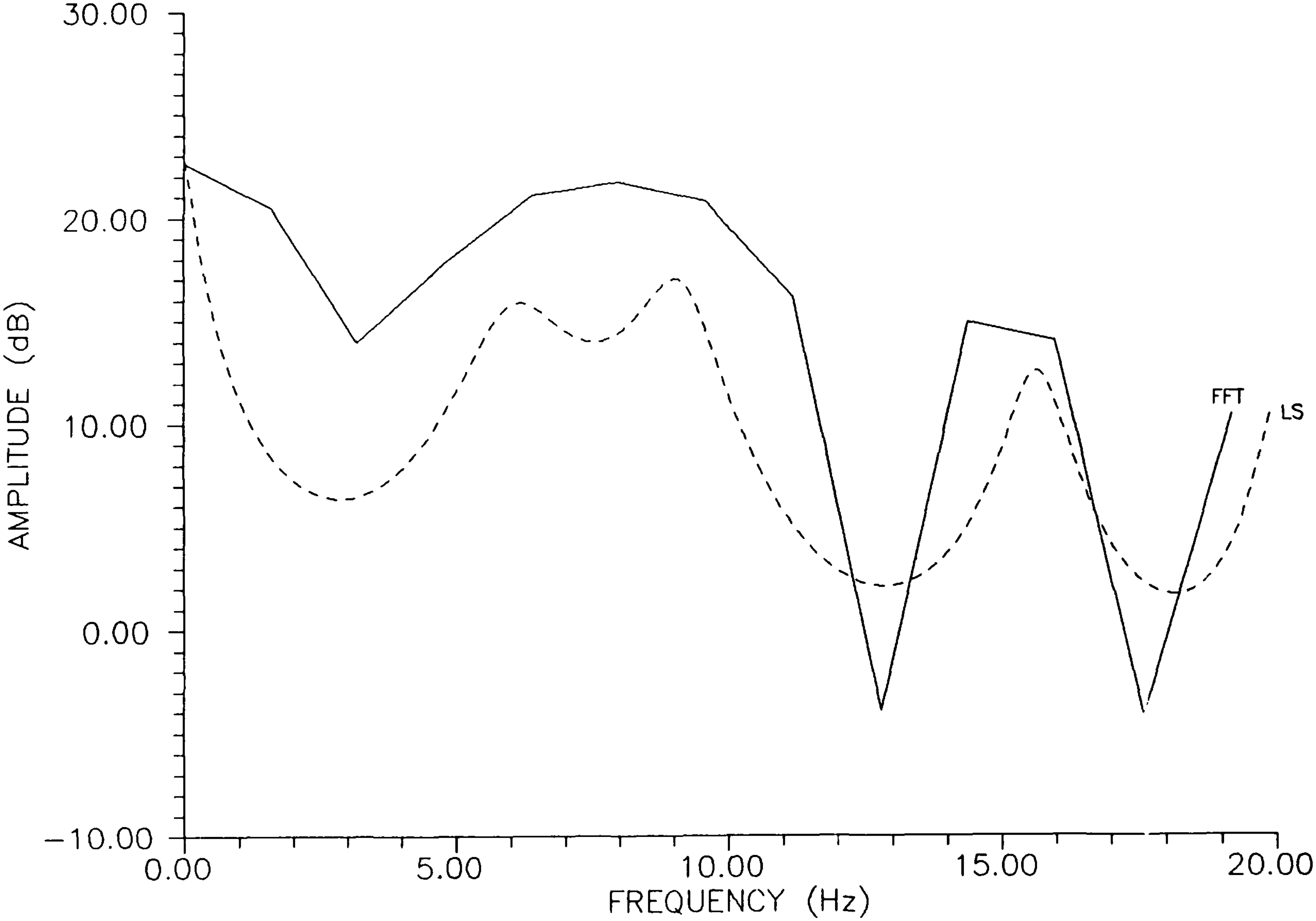

Figure A-16. LS and FFT Spectral Estimates of Actual EEG Data.

analysis of deterministic signals could be used to say that the width of the peaks for the LS estimate are probably more accurate.

Figure A-14 illustrates another case where the estimates are very similar. As was seen in Figure A-4, the LS estimate is smoother but the estimates have nearly the same shape.

The FFT estimate shown in Figure A-15 has four very gentle peaks in the spectrum. The LS estimate also shows four peaks in the spectrum. Three of the peaks are similar to the FFT estimate in terms of amplitude and sharpness. However, the peak near 7 Hz is much sharper and larger in amplitude than for the FFT estimate. The characteristic that the FFT produces a better estimate of the relative amplitude of peaks, seen for the deterministic signals, might be used here to say that the peak near 7 Hz is smaller than indicated by the LS estimate.

Figure A-16 again shows estimates which are very similar. The important difference in this case is that the LS estimate indicates two peaks in the region between 5-10 Hz while the FFT estimate shows one broad peak in this region. It is known that the LS method has superior frequency resolution capabilities and it looks as though the FFT may not be able to resolve the closely spaced peaks.

The above results should help illustrate how insight gained from the analysis of deterministic signals can be used to analyze signals with unknown spectra. They also illustrate how the two spectral estimation methods can be used in conjunction with each other to estimate an unknown spectrum.

D <u>Summary</u>

The preceding text contained many concepts concerning techniques for estimating the spectrum of a signal. Particular attention has been given to the differences between FFT-based and Model-based methods when used for analyzing short records of EEG data. Each method has strengths and weaknesses. The FFT-based approaches have problems when dealing with very noisy signals, and with short data records. Modern methods, on the other hand do not do well at estimating absolute power, and can produce extreme errors if the model is poorly selected. Indeed, the research suggests that a hybrid algorithm, employing information from both estimators could be of considerable merit.

APPENDIX A (continued)

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APPENDIX B

Details of Relax Condition, Read Condition, and Lexical Decision Task

A. Stimuli

1. Read Condition

The stimuli used in the Read Task were two text passages, each about 750 words in length. Each passage was presented on the visual display. Subjects pressed a response key to display a new page of text. A set of eight multiple choice questions concerning each passage was composed. The text passages and the question sets are included in Green, West, and Engler (1986).

2. Lexical Decision Task

This task required the subject to decide whether a four-letter string comprised a word or nonword. The stimuli used for this task were selected from those used in previous A.R.I.-sponsored research (Green, 1985), where they were associated with a reliable right visual field advantage.

The word items were four-letter, one-syllable nouns. Half of the words were concrete nouns and half were abstract nouns, as determined by a brief ratings study (see Green, 1985, for details). The nonwords were created by taking each word item and recombining its letters to create a one-syllable, pronounceable nonword. Homophones of real words were not used. The stimulus lists can be found in Green, West, and Engler (1986).

The stimulus list was divided into three blocks of 64 trials each. Each block consisted of 16 of the concrete words, 16 of the abstract words of similar frequency, and the 32 nonwords formed from the letters of each word. Half of each item type was designated for presentation in the right visual field and half of the same type of similar frequency was designated for the left visual field. Both item type and item visual field were randomly ordered within a trial block. There was also one practice trial block of 32 items composed similarly to the test trial block.

Each letter measured 5.0 mm by 5.0 mm. The letters in each item were arrayed horizontally, with the inner edge of the most central letter (in either visual field) being 13.0 mm from the fixation point. There was 1.0 mm between the letters within each item. The letters were vertically positioned on the horizontal axis through the fixation point. Since subjects viewed from a distance 500.0 mm from the display, the

four-letter item appeared between 1.49 to 4.12 degrees of visual angle.

B. Procedure for Subject Testing

1. Relax Condition

Each subject was instructed to place his head in the headrest, to close his eyes, and to relax. He was asked to keep tongue, eye, and body movement at a minimum. This condition lasted four minutes.

2. Read Condition

The subject was asked to place his head in the headrest and to read the text presented on the visual display before him. He was allowed to move his eyes naturally in order to read. The reading lasted for four minutes. To validate that reading and comprehension had occurred, the subject was asked to respond to a set of eight questions about the text material.

3. Lexical Decision Task

Within each test session, each subject was presented with one practice block (32 trials) and three test blocks (64 trials each). Each test trial proceeded as follows. A small fixation plus appeared in the center of the screen. The subject was instructed to carefully fixate on the plus, and when fixated to press both response keys to initiate the trial. The fixation plus remained on, but 500 ms later a stimulus item appeared for 150 ms in the left or right visual field. The stimulus was immediately followed by a 150 ms mask. The mask consisted of four square patches, one overlaying each of the areas in which a stimulus letter had appeared. Each patch looked like a very dense array of fine, bright dots and was created by lighting all of the CRT pixels in the area over each letter. The fixation plus disappeared with the offset of the mask. The subject's task was to judge whether each item was a word or a nonword, and to indicate the decision with an appropriate keypress. Following response, performance feedback (either the correct reaction time or the word "ERROR") appeared for one second in the center of the screen above the former location of the plus. The plus then reappeared signalling the beginning of a new trial.

After each test block subjects were encouraged to lower their error rate if it had exceeded 25 percent for that block. They were also asked to reduce eye or body movement if observation of the EEG write-out indicated that these were

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occurring at inappropriate times (e.g., during stimulus presentation) or were causing artifacts in the EEG data.

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APPENDIX C

Behavioral Assessment

The purpose of the behavioral assessment was to collect data on some dimensions which have been proposed as indices of brain organization (see Bryden, 1982). Such indices might be useful in interpreting individual differences in performance.

The indices used were handedness, eye dominance, tapping speed, and foot dominance. Handedness was assessed through use of a self-report measure, a modified Edinburgh Handedness Inventory (Oldfield, 1971) and through use of a performance measure, relative finger tapping speed. The handedness inventory generates handedness scores between 11 and 60, where 60 represents very strong right handedness. Relative finger tapping speed is a measure derived from neuropsychological assessment procedures for determining the locus of brain damage in the left or right hemisphere (Lezak, 1983). It is assessed by computing the difference between the hands in the average tapping rate for three, ten-second tapping trials.

Footedness was assessed through the use of two procedures -- the Stamping Test (Harris, 1957) and the Kicking Test. The Stamping Test requires subjects to stamp on a small disk placed in front of them. The foot used to stamp the small disk is inferred as the dominant one. The Kicking Test requires subjects to kick a ball at a small disk mourted on a wall. The foot used to kick is inferred as dominant. By giving one point for each left foot response and two points for each right foot response (Searleman, 1980), subjects can be classified as left dominant (total points = 2), mixed dominant (total points = 3), or right dominant (total points = 4).

Both foveal and peripheral acuity were assessed to insure that subjects had at least 20/40 vision at a distance of twenty feet and accurate peripheral acuity to at least five degrees, either corrected or uncorrected. Eye dominance was measured by identifying the eye used to sight a distant object through a small hole in a piece of paper.

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APPENDIX D

Subject Characteristics

Subject	Footedness	Eye Dominance	Handedness Mother	Handedness Father	Handedness Score	Tapping Score Left	Tapping Score Right
1	2	R	R	R	36	49.5	52.3
2	2	R	R	R	16	51.3	51.0
3	4	L	R	R	27	55.7	52.3
4	2	L	R	R	27	63.7	55.7
5	2	R	R	R	28	44.3	44.0
6	4	L	R	R	36	51.3	57.7
7	3	R	R	R	32	56.3	52.0
8	2	L	L	A	19	70.7	69.3
9	3	L	R	R	28	61.0	55.3
10	3	R	R	R	32	52.7	53.0
11	4	R	R	L	25	52.0	46.3
12	2	L	R	R	33	54.0	46.0
13	4	L	R	R	34	58.7	57.3
14	2	L	R	R	22	58.7	76.0
15	3	R	R	R	28	56.7	61.3
16	4	L	R	R	28	54.0	47.0
17	3	R	R	L	33	50.3	47.7
18	2	L	R	R	17	47.0	44.0
19	2	L	R	L	18	61.3	51.7
20	2	L	?	R	23	51.0	44.3
21	4	R	R	R	54	55.0	57.0
22	4	R	R	R	45	50.3	60.0
23	4	L	R	R	53	47.7	50.3
24	3	R	R	R	49	46.3	53.3
25	4	L	R	R	45	46.3	54.3
26	4	L	R	R	55	63.0	65.0
27	4	L	R	R	54	52.3	54.0
28	4	L	R	R	56	58.0	62.0
29	4	R	R	R	47	52.0	61.0
30	4	L	R	R	54	48.0	50.7
31	4	L	R	R	45	47.0	47.0
32	4	R	R	L	50	49.0	49.6
33	4	R	R	R	50	59.7	69.3
34	3	R	R	R	46	45.3	43.7
35	4	R	R	R	54	50.7	56.7
36	4	R	R	R	54	53.0	58.3
37	3	R	R	R	52	49.3	53.3
38	4	R	R	R	50	44.0	49.3
39	4	R	R	R	45	64.3	69.3
40	4	L	R	R	53	43.3	51.0

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APPENDIX E

Lexical Decision Task: Reaction Time (ms) and Error

Reaction Time:

Stimulus Type -->	Abstract Word		Concrete Word		Nonword		Overall	
Visual Field -->	L	R	L	R	L	R	L	R
Subject								
1	760	598	722	618	787	675	756	630
2	978	998	940	789	983	815	967	867
3	945	887	1011	717	1198	923	1051	842
4	722	599	760	649	927	840	803	696
5	960	880	930	893	850	1027	913	933
6	750	688	753	642	737	756	747	695
7	601	675	597	793	784	906	661	791
8	631	515	678	506	709	661	673	561
9	614	495	572	517	671	689	619	567
10	726	722	830	747	871	915	809	795
11	911	737	937	707	841	936	896	793
12	869	645	822	694	782	747	824	695
13	663	565	678	573	689	718	677	619
14	558	601	547	588	645	665	583	618
15	1138	808	803	829	1121	1135	1021	924
16	1138	785	877	788	1586	1601	1200	1058
17	740	649	722	613	708	712	723	658
18	812	713	790	748	930	901	844	787
19	768	721	869	619	904	715	847	685
20	861	721	723	771	966	871	850	788
21	728	802	796	778	947	799	824	793
22	504	503	499	493	604	556	536	517
23	824	749	811	786	750	701	795	745
24	747	709	800	722	801	756	783	729
25	760	693	684	664	885	765	776	707
26	873	783	851	774	993	930	906	829
27	614	610	731	654	834	708	726	657
28	812	807	921	751	1157	1255	963	938
29	614	511	577	586	659	596	617	564
30	701	703	745	694	851	880	766	759
31	625	597	602	646	686	732	638	658
32	625	597	602	646	686	732	638	658
33	561	539	605	621	613	586	593	582
34	810	719	725	704	784	718	773	714
35	1519	1261	1473	1248	1310	1270	1434	1260
36	867	835	889	856	998	900	918	864
37	723	722	713	645	809	732	748	700
38	745	748	759	766	797	813	767	776
39	907	813	910	758	1171	944	996	838
40	741	737	666	681	969	818	792	745

APPENDIX E (concluded)

<u>Percentage of Error:</u>

Stimulus Type -->	Abstract Word		Concrete Word		Nonword		Overall	
Visual Field -->	L	R	L	R	L	R	L	R
Subject								
1	37.50	16.67	33.33	4.17	35.42	16.67	35.42	12.50
2	45.83	37.50	29.17	8.33	22.92	8.33	32.64	18.05
3	16.67	16.67	25.00	12.50	16.67	18.75	19.45	15.97
4	8.33	8.33	33.33	12.50	33.33	25.00	25.00	15.28
5	12.50	12.50	20.83	25.00	16.67	25.00	16.67	20.83
6	20.83	20.83	20.83	8.33	20.83	22.92	20.83	17.36
7	4.17	20.83	16.67	12.50	12.50	18.75	11.11	17.36
8	37.50	0.00	20.83	4.17	22.92	16.67	27.08	6.95
9	20.83	0.00	12.50	0.00	14.58	14.58	15.97	4.86
10	25.00	8.33	4.17	12.50	29.17	22.92	19.45	14.58
11	4.17	4.17	8.33	0.00	8.33	0.00	6.94	1.39
12	8.33	8.33	12.50	4.17	18.75	16.67	13.19	9.72
13	8.33	12.50	20.83	4.17	10.42	12.50	13.19	9.72
14	0.00	12.50	4.17	8.33	4.17	8.33	2.78	9.72
15	33.33	8.33	12.50	8.33	27.08	37.50	24.30	18.05
16	25.00	12.50	20.83	8.33	25.00	12.50	23.61	11.11
17	41.67	4.17	29.17	0.00	16.67	6.25	29.17	3.47
18	16.67	4.17	25.00	0.00	12.50	22.92	18.06	9.03
19	41.67	20.83	33.33	8.33	10.42	10.42	28.47	13.19
20	20.83	25.00	12.50	16.67	22.92	14.58	18.75	18.75
21	29.17	4.17	12.50	4.17	18.75	8.33	20.14	5.56
22	8.33	16.67	4.17	4.17	10.42	8.33	7.64	9.72
23	20.83	12.50	16.67	4.17	6.25	8.33	14.58	8.33
24	4.17	0.00	8.33	8.33	25.00	10.42	12.50	6.25
25	12.50	8.33	8.33	4.17	12.50	10.42	11.11	7.64
26	20.83	8.33	20.83	8.33	16.67	16.67	19.44	11.11
27	16.67	8.33	12.50	16.67	35.42	29.17	21.53	18.06
28	8.33	4.17	25.00	4.17	14.58	10.42	15.97	6.25
29	16.67	8.33	12.50	12.50	12.50	14.58	13.89	11.80
30	4.17	4.17	4.17	0.00	16.67	12.50	8.34	5.56
31	25.00	4.17	12.50	8.33	12.50	14.58	16.67	9.03
32	25.00	4.17	12.50	8.33	12.50	14.58	16.67	9.03
33	25.00	8.33	20.83	0.00	27.08	22.92	24.30	10.42
34	25.00	20.83	41.67	8.33	31.25	18.75	32.64	15.97
35	4.17	12.50	12.50	12.50	14.58	16.67	10.42	13.89
36	12.50	4.17	8.33	4.17	6.25	6.25	9.03	4.86
37	12.50	8.33	16.67	12.50	18.75	14.58	15.97	11.80
38	37.50	12.50	20.83	4.17	29.17	29.17	29.17	15.28
39	29.17	12.50	20.83	0.00	20.83	16.67	23.61	9.72
40	8.33	8.33	8.33	4.17	16.67	10.42	11.11	7.64

APPENDIX

Method for EEG Data Collection and Analysis

A. Collection of Calibration Data

Calibration data were collected for use in determining whether there were differences in gain between the EEG channels, and to allow adjustment for any differences.

B. Procedure for EEG Data Collection

EEG activity was monitored throughout the testing by observation of the paper write-out from the EEG machine. It was impractical to continuously collect and store EEG data throughout each session because the required data storage requirements would be enormous. A subset of the data was therefore collected and stored for subsequent analysis.

During performance of the lexical decision task, EEG data collection for each trial was initiated by the keypress indicating visual fixation at the beginning of the trial and was terminated by the keypress response indicating the subject's word-nonword decision. During the Read and Relax conditions, EEG data were collected and stored for alternate four second intervals.

C. Review of Data

In using EEG data to understand human cognition and performance, an important first step in data analysis involves review of the data to eliminate contaminated data samples. The goal is to include in data analysis samples which are primarily a function of the cerebral activity of interest, e.g., that associated with lexical decision-making, and to exclude samples which are predominated by less interesting activity, e.g., irrelevant muscle movement.

For each of the Relax and Read conditions, a total of thirty samples of EEG data, each four seconds in length, was collected during each test session. The paper write-outs were visually reviewed by the neurologist on the research team to eliminate data samples which had been contaminated by artifact. Typical factors causing artifact were large eye movements, motor movement, or temporary detachment of electrodes.

For the lexical decision task, a total of 192 samples of EEG data was collected during each session. The length of the sample varied as a function of the subject reaction time. These samples were also reviewed for artifact. In addition, the write-out from the EEG machine channel recording eye

movement was used to eliminate samples during which an inappropriate eye movement had occurred. An inappropriate eye movement was identified as one that had occurred within the first 600 ms of the data sample, i.e., between the initiation of the "ready" keypress and the offset of the stimulus. Samples for which the subject response had been incorrect were also eliminated.

The number of samples analyzed for each subject for each condition are indicated at the end of this Appendix.

D. Assessment of Power Within the Alpha Band

A Fast Fourier Transform (Rader, 1979) was used to compute the spectral distribution for valid data. The spectral distribution describes power as a function of frequency, and was used to infer the power within the alpha band. It is important to note that because gains in the measurement system were not assessed, power is in terms of relative (rather than absolute) watts. The relative level of power is a reflection of the level of alpha activity.

One important decision in applying the FFT involved choosing the time interval for analysis, or the "window size." Window size is directly related to the frequency resolution of the spectral distribution obtained from the FFT -- as window size increases, the frequency resolution increases. However, using very large windows has a negative impact because this reduces the number of estimates of power obtained from the data. Smaller windows generally provide more estimates. Window sizes of one-half to two seconds long are generally used.

For the Read and Relax conditions, it was decided to apply two, non-overlapping two-second windows to each four second sample. This provided two estimates of the spectral distribution for each four second sample, with a one-half Hz frequency resolution for frequencies between one and fifty Hz. The power for frequencies between eight and twelve Hz was summed to obtain an estimate of the power within the alpha band.

For the lexical decision task, application of the FFT was complicated by the fact that sample lengths varied as a function of reaction time. The validity of the FFT for estimating spectral parameters depends on having constant sample sizes. In addition, many of the samples were relatively short (less than 750 ms), thus reducing the frequency resolution.

APPENDIX F (concluded)

It was decided to analyze constant-size intervals that would be available from each data sample, regardless of reaction time. The FFT was applied to the 250 ms interval just before stimulus onset (pre-stimulus interval) and to the 250 ms interval immediately after stimulus onset (post-stimulus interval). The pre-stimulus interval represents a period when the subject should be aroused to process the stimulus. The post-stimulus interval represents a period when the subject is actively processing the stimulus.

Analysis of 250 ms intervals results in a four Hz frequency resolution. It was therefore possible to infer the power within the alpha band (8-12 Hz). It was not possible to infer the power associated with specific frequencies within that range, e.g., the power from 9-10 Hz. This was not problematic, however, since the major interest was in overall power within the alpha band.

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APPENDIX G

Relax Condition: Median Alpha (watts) for Each Subject

Hemisphere -->	Left			Right			Asymmetry (Right - Left)		
Location -->	Temp.	Cent.	Par.	Temp.	Cent.	Par.	Temp.	Cent.	Par.
Subject									
1	10.00	20.90	32.00	9.80	25.30	29.75	-0.20	4.90	-2.25
2	7.70	32.75	26.05	10.70	32.10	34.05	3.00	-0.65	8.00
3	18.45	40.95	112.05	16.70	44.25	113.50	-1.75	3.30	1.45
4	33.75	129.70	142.00	20.65	133.60	151.40	-13.10	3.90	9.40
5	13.45	30.05	49.55	23.20	37.10	55.65	9.75	7.05	6.10
6	17.00	44.35	137.35	38.95	89.25	225.60	21.95	44.90	88.25
7	5.10	26.65	106.20	9.30	35.60	124.45	4.20	8.95	18.25
8	38.85	79.40	125.30	17.45	78.70	114.80	-21.40	-0.70	-10.50
9	13.75	74.40	168.05	21.95	66.10	184.45	8.20	-8.30	16.40
10	15.60	31.70	34.75	13.40	28.95	40.75	-2.20	-2.75	6.00
11	18.60	50.15	93.60	32.90	74.55	116.35	14.30	24.40	22.75
12	7.00	20.65	33.10	9.70	25.60	44.35	2.70	4.95	11.25
13	11.90	24.75	48.50	10.20	22.15	59.45	-1.70	-2.60	10.95
14	4.95	14.95	11.25	6.55	13.80	12.00	1.60	-1.15	0.75
15	7.35	22.30	53.10	8.40	23.05	68.85	1.05	0.75	15.75
16	17.60	64.30	161.35	23.20	72.30	173.65	5.60	8.00	12.30
17	28.70	47.50	67.80	14.35	29.35	55.70	-14.35	-18.15	-12.10
18	44.10	46.70	67.05	25.55	57.35	103.55	-18.55	10.65	36.50
19	43.75	153.10	216.70	27.95	151.60	184.95	-15.80	-1.50	-31.75
20	17.05	54.05	61.65	24.45	57.20	80.35	7.40	3.15	18.70
21	16.05	56.55	138.55	12.20	35.55	52.10	-3.85	-21.00	-86.45
22	18.35	74.25	135.80	18.15	63.75	210.05	-0.20	-10.50	74.25
23	25.95	64.15	76.25	25.30	68.20	73.05	-0.65	4.05	-3.20
24	6.20	17.90	18.35	8.75	21.80	19.60	2.55	3.90	1.25
25	3.25	15.55	16.95	3.55	11.00	16.90	0.30	-4.55	-0.05
26	8.15	17.90	74.50	7.40	33.55	42.50	-0.75	15.65	-32.00
27	16.90	30.35	42.50	13.15	45.55	61.20	-3.75	15.20	18.70
28	11.05	39.25	115.40	19.05	62.40	237.85	8.00	23.15	122.45
29	31.70	95.30	168.90	60.95	130.50	217.10	29.25	35.20	48.20
30	46.85	218.30	362.85	68.65	264.75	399.60	21.80	46.45	36.75
31	9.20	18.20	22.95	7.05	25.90	42.45	-2.15	7.70	19.50
32	19.75	31.60	36.95	10.60	38.65	56.15	-9.15	7.05	19.20
33	8.10	19.65	48.05	11.30	30.65	82.30	3.20	11.00	34.25
34	11.35	28.90	46.45	12.35	28.60	43.25	1.00	-0.30	-3.20
35	17.75	70.25	93.40	17.25	42.90	58.00	-0.50	-27.35	-35.40
36	8.10	17.05	17.95	6.05	17.25	17.00	-2.05	0.20	-0.95
37	3.20	12.40	17.70	8.30	20.45	34.80	5.10	8.05	17.10
38	27.00	74.55	122.65	16.40	47.35	165.80	-10.60	-27.20	43.15
39	26.20	56.40	126.80	55.75	73.90	237.80	29.55	17.50	111.00
40	9.50	31.85	45.00	12.15	44.90	65.25	2.65	13.05	20.25

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APPENDIX H

Read Condition: Median Alpha (watts) for Each Subject

Hemisphere -->	Left			Right			Asymmetry (Right - Left)		
Location -->	Temp.	Cent.	Par.	Temp.	Cent.	Par.	Temp.	Cent.	Par.
Subject									
1	7.50	18.80	18.30	6.85	18.45	17.60	-0.65	-0.35	-0.70
2	5.05	16.00	11.60	4.75	14.70	13.00	-0.30	-1.30	1.40
3	7.50	21.35	25.05	8.30	18.15	21.90	0.80	-3.20	-3.15
4	11.30	22.80	46.95	10.35	28.50	51.80	-0.95	5.70	4.85
5	10.75	17.15	29.80	11.50	18.45	27.35	0.75	1.30	-2.45
6	11.60	23.20	29.80	19.15	40.60	41.85	7.55	17.40	12.05
7	2.25	11.30	13.25	5.75	11.55	12.80	3.50	0.25	-0.45
8	17.85	21.10	22.25	5.80	15.00	17.15	-12.05	-6.10	-5.10
9	5.85	16.80	15.10	4.85	9.75	12.00	-1.00	-7.05	-3.10
10	8.05	13.25	15.55	10.90	16.45	18.65	2.85	3.20	3.10
11	18.50	43.40	69.75	21.85	72.00	96.55	3.35	28.60	26.80
12	6.70	8.95	10.50	6.15	9.15	9.95	-0.55	0.20	-0.55
13	5.70	8.30	11.85	4.85	7.85	10.40	-0.85	-0.45	-1.45
14	2.90	4.90	4.85	2.10	4.80	4.50	-0.80	-0.10	-0.35
15	6.25	11.80	16.65	6.50	11.20	10.45	0.25	-0.60	-6.20
16	4.45	14.05	31.20	8.90	25.00	53.15	4.45	10.95	21.95
17	15.45	20.60	20.60	14.05	14.55	19.90	-1.40	-6.05	-0.70
18	21.00	19.80	28.15	8.30	13.30	17.75	-12.70	-6.50	-10.40
19	12.05	35.65	45.80	8.75	16.20	19.10	-3.30	-19.45	-26.70
20	5.85	7.40	9.10	8.85	8.35	9.60	3.00	0.95	0.50
21	7.05	13.75	12.65	8.50	20.85	16.75	1.45	7.10	4.10
22	13.65	24.80	40.75	15.55	21.55	38.15	1.90	-3.25	-2.60
23	6.80	14.05	29.65	19.25	24.05	31.00	12.45	10.00	1.35
24	6.80	3.50	14.65	6.20	11.85	14.60	-0.60	-1.65	-0.05
25	4.25	13.60	14.95	4.40	11.50	12.05	0.15	-2.10	-2.90
26	(data unavailable due to technical problems)								
27	7.85	9.65	12.05	8.05	12.45	15.30	0.20	2.80	3.25
28	3.95	9.60	12.70	5.70	11.90	16.55	1.75	2.30	3.85
29	20.20	46.10	93.80	46.30	57.90	80.50	26.10	11.80	-13.30
30	19.00	91.15	192.30	23.75	79.55	103.90	4.75	-11.60	-88.40
31	3.85	7.00	7.45	3.35	8.60	8.70	-0.50	1.60	1.25
32	10.90	9.10	13.25	4.90	13.15	16.55	-6.00	4.05	3.30
33	5.00	10.05	15.85	7.20	15.75	19.15	2.20	5.70	3.30
34	5.65	9.95	10.50	5.60	9.95	9.65	-0.05	0.00	-0.85
35	10.05	30.65	47.50	11.35	27.05	35.10	1.30	-3.60	-12.40
36	8.65	13.00	12.05	8.20	18.40	15.20	-0.45	5.40	3.15
37	2.05	4.75	7.05	6.60	10.55	8.95	4.55	5.80	1.90
38	4.65	7.05	7.35	4.20	6.70	8.75	-0.45	-0.35	1.40
39	10.50	30.25	49.75	17.15	46.30	58.75	6.65	16.05	9.00
40	7.30	10.60	16.80	7.50	12.90	15.35	0.20	2.30	-1.45

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APPENDIX I

Lexical Decision Task: Median Alpha (watts) for Each Subject

Pre-stimulus Interval:									
Hemisphere -->	Left			Right			Asymmetry (Right - Left)		
Location -->	Temp.	Cent.	Par.	Temp.	Cent.	Par.	Temp.	Cent.	Par.
Subject									
1	7.60	9.10	9.30	6.90	10.20	12.80	-0.70	1.10	3.50
2	10.35	16.35	20.65	7.80	16.75	20.40	-2.55	0.40	-0.25
3	5.95	6.85	10.30	6.15	7.45	7.75	0.20	0.60	-2.55
4	14.50	32.25	34.95	8.80	26.90	42.75	-5.70	-5.35	7.80
5	10.85	10.70	12.55	10.85	11.60	11.40	0.00	0.90	-1.15
6	11.40	17.40	33.50	20.30	28.10	67.35	8.90	10.70	33.85
7	2.80	8.55	11.30	5.35	7.75	12.25	2.55	-0.80	0.95
8	16.40	15.50	14.90	4.50	12.00	15.20	-11.90	-3.50	0.30
9	1.25	0.50	0.55	1.35	0.60	0.50	0.10	0.10	-0.05
10	12.05	8.75	11.40	5.00	10.20	9.85	-7.05	1.45	-1.55
11	12.80	15.85	23.70	18.95	18.80	35.70	6.15	2.95	12.00
12	3.30	6.30	8.90	2.70	6.30	6.60	-0.60	0.00	-2.30
13	6.85	7.90	9.60	5.75	6.75	8.55	-1.10	-1.15	-1.05
14	2.10	3.60	3.80	1.50	2.90	3.70	-0.60	-0.70	-0.10
15	7.90	7.40	7.90	9.20	10.00	8.50	1.30	2.60	0.60
16	6.90	11.40	30.50	5.50	11.00	27.80	-1.40	-0.40	-2.70
17	30.20	18.90	17.40	13.60	13.90	19.30	-16.60	-5.00	1.90
18	24.90	17.25	22.05	10.85	14.35	16.80	-14.05	-2.90	-5.25
19	8.80	13.10	15.00	7.30	13.80	17.30	-1.50	0.70	2.30
20	5.60	8.60	9.85	10.60	10.30	13.70	5.00	1.70	3.85
21	5.95	7.90	9.00	5.00	6.50	7.25	-0.95	-1.40	-1.75
22	8.90	13.80	13.10	7.50	12.90	14.90	-1.40	-0.90	1.80
23	16.10	11.10	14.10	12.30	20.30	20.80	-3.80	9.20	6.70
24	6.50	10.70	10.90	6.20	8.85	10.85	-0.30	-1.85	-0.05
25	4.05	7.60	9.20	5.30	8.15	10.15	1.25	0.55	0.95
26	5.90	7.10	6.10	6.65	6.35	6.80	0.75	-0.75	0.70
27	13.55	8.45	10.40	7.65	10.50	7.90	-5.90	2.05	-2.50
28	3.55	8.95	12.05	7.30	15.10	18.20	3.75	6.15	6.15
29	14.25	30.15	54.05	28.15	46.25	84.05	13.90	16.10	30.00
30	9.25	24.60	32.20	10.00	22.40	43.10	0.75	-2.20	10.90
31	7.90	9.00	12.90	6.50	10.10	13.20	-1.40	1.10	0.30
32	10.30	9.65	10.85	7.10	14.45	15.45	-3.20	4.80	4.60
33	3.40	7.70	8.10	5.10	9.50	18.80	1.70	1.80	10.70
34	5.00	8.60	13.70	7.90	12.00	16.70	2.90	3.40	3.00
35	5.10	5.90	6.95	6.25	7.95	8.40	1.15	2.05	1.45
36	7.20	7.95	8.20	7.60	6.95	7.85	0.40	-1.00	-0.35
37	1.45	4.40	4.25	5.00	6.35	5.05	3.55	1.95	0.80
38	7.80	18.70	20.55	9.40	18.70	41.45	1.60	0.00	20.90
39	14.10	19.70	32.30	20.70	31.20	49.40	6.60	11.50	17.10
40	7.15	11.50	16.85	8.15	14.45	16.65	1.00	2.95	-0.20

APPENDIX I (concluded)

Post-stimulus interval:									
Hemisphere -->		Left			Right			Asymmetry (Right - Left)	
Location -->	Temp.	Cent.	Par.	Temp.	Cent.	Par.	Temp.	Cent.	Par.
Subject									
1	10.30	12.10	13.70	7.10	11.40	15.30	-3.20	-0.70	1.60
2	7.10	12.45	16.45	8.75	13.35	19.60	1.65	0.90	3.15
3	7.00	11.85	17.50	5.80	18.85	23.25	-1.20	7.00	5.75
4	12.90	28.40	36.45	6.85	29.55	36.35	-6.05	1.15	-0.10
5	13.70	18.60	25.55	12.20	20.20	27.65	-1.50	1.60	2.10
6	14.60	21.70	40.10	15.80	32.05	46.85	1.20	10.35	6.75
7	2.25	6.90	13.95	4.15	9.55	15.50	1.90	2.65	1.55
8	13.20	15.30	18.00	6.50	10.40	16.30	-6.70	-4.90	-1.70
9	0.30	0.30	0.30	0.40	0.35	0.30	0.10	0.05	0.00
10	14.45	7.60	9.70	6.35	11.70	10.10	-8.10	4.10	0.40
11	11.45	13.00	22.50	17.60	22.55	37.05	6.15	9.55	14.55
12	3.60	9.90	18.70	7.20	16.30	25.70	3.60	6.40	7.00
13	11.10	12.65	20.70	6.35	10.55	17.15	-4.75	-2.10	-3.55
14	3.50	5.00	4.50	1.60	5.10	4.40	-1.90	0.10	-0.10
15	9.30	14.60	15.00	14.60	13.40	31.10	5.30	-1.20	16.10
16	3.30	7.20	26.70	5.60	12.10	33.40	2.30	4.90	6.70
17	27.60	25.80	29.20	13.30	25.40	31.80	-14.30	-0.40	2.60
18	29.60	19.15	21.05	11.65	17.65	20.20	-17.95	-1.50	-0.85
19	10.80	13.10	10.60	5.60	13.30	13.40	-5.20	0.20	2.80
20	7.00	9.35	12.00	9.05	10.95	14.35	2.05	1.60	2.35
21	5.50	7.95	8.50	5.45	7.75	7.80	-0.05	-0.20	-0.70
22	6.60	10.60	13.20	9.30	14.90	15.90	2.70	4.30	2.70
23	13.80	11.70	18.30	15.00	21.30	25.40	1.20	9.60	7.10
24	7.85	9.50	9.85	6.65	8.70	14.30	-1.20	-0.80	4.45
25	3.50	11.95	13.00	4.35	11.10	13.45	0.85	-0.85	0.45
26	5.10	11.50	8.05	8.20	10.75	13.70	3.10	-0.75	5.65
27	14.05	7.85	10.95	6.60	9.10	12.85	-7.45	1.25	1.90
28	3.75	10.70	12.70	5.45	11.55	15.40	1.70	0.85	2.70
29	12.35	19.35	39.50	23.35	33.30	69.00	11.00	13.95	29.50
30	6.15	22.05	49.35	11.60	29.85	64.00	5.45	7.80	14.65
31	7.60	6.40	8.30	6.40	6.60	13.10	-1.20	0.20	4.80
32	12.10	8.90	10.90	8.70	17.20	23.00	-3.40	8.30	12.10
33	5.20	7.10	7.80	5.70	8.00	12.10	0.50	0.90	4.30
34	4.30	7.60	11.80	8.20	8.70	14.30	3.90	1.10	2.50
35	5.70	5.45	7.55	7.00	8.65	7.20	1.30	3.20	-0.35
36	7.80	7.85	11.05	5.65	7.50	9.25	-2.15	-0.35	-1.80
37	1.30	4.30	10.35	3.75	5.15	10.80	2.45	0.85	0.45
38	6.35	13.15	14.50	6.25	10.30	20.10	-0.10	-2.85	5.60
39	10.60	16.00	20.90	15.00	20.50	32.20	4.40	4.50	11.30
40	8.85	13.30	17.20	6.10	15.55	17.25	-2.75	2.25	0.05

APPENDIX J

ERPs: Peak Amplitude (volts) and Peak Time (ms) for Each Subject

Location -->	Central				Parietal			
Measure -->	Peak Amp		Peak Time		Peak Amp		Peak Time	
Hemi.-->	Left	Right	Left	Right	Left	Right	Left	Right
Subject								
1	43.67	47.79	399	399	33.87	57.13	404	417
2	12.91	13.50	421	439	21.52	17.84	423	370
3	40.46	76.56	411	382	52.67	91.74	410	384
4	20.98	34.45	385	422	33.79	46.75	421	422
5	46.53	46.05	439	439	54.67	68.32	448	439
6	42.00	62.44	404	404	54.70	72.72	404	404
7	19.85	25.23	379	343	32.86	29.91	387	387
8	45.46	60.24	424	423	55.53	72.11	427	427
9	16.31	18.74	415	416	12.34	16.87	407	416
10	19.29	12.72	415	419	24.59	34.27	430	430
11	19.43	30.68	424	430	36.32	48.36	424	440
12	31.75	42.21	402	396	29.59	58.71	369	369
13	22.26	29.86	448	449	40.43	50.43	448	449
14	18.37	15.34	423	423	16.47	12.31	412	418
15	48.45	42.38	380	401	29.52	34.31	365	373
16	25.32	18.75	447	443	43.31	48.06	405	402
17	63.76	59.40	408	409	64.47	59.65	408	413
18	26.44	38.37	381	380	24.42	31.17	381	380
19	11.62	38.47	415	408	23.81	45.77	418	411
20	27.80	38.19	361	363	31.51	35.68	378	369
21	22.29	48.08	421	424	51.09	56.20	424	424
22	33.49	28.23	445	444	44.22	41.16	440	443
23	7.47	25.03	381	391	25.24	19.47	444	448
24	49.57	54.16	435	433	75.38	73.46	482	481
25	39.83	53.89	353	353	41.29	47.69	423	422
26	32.67	41.79	385	393	21.65	34.63	428	428
27	30.08	35.64	404	417	35.23	37.42	417	417
28	35.90	62.28	355	355	38.21	64.48	425	424
29	32.55	52.27	416	406	59.10	80.53	415	403
30	45.14	65.84	387	387	50.83	67.70	381	381
31	10.68	5.99	430	426	25.92	11.58	434	391
32	8.87	26.55	427	428	19.12	32.08	431	427
33	62.92	55.22	392	375	62.81	69.23	376	411
34	41.62	38.89	419	419	41.70	32.59	428	428
35	(data unavailable)							
36	36.55	41.86	425	420	37.90	44.17	425	424
37	17.04	20.89	390	382	36.78	46.15	393	392
38	35.92	38.21	385	397	22.24	22.15	396	397
39	39.81	39.94	404	392	51.54	56.10	413	412
40	(data unavailable)							

END
DATE
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